THE IMPACT OF FINANCIAL AND NON-FINANCIAL MEASURES ON BANKS' FINANCIAL STRENGTH RATINGS: THE CASE OF THE MIDDLE EAST

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List of Contents

Table of Contents	i
List of Figures	vi
List of Tables	vii
List of Abbreviations and Terms	x
Acknowledgements	xi
Author's Declaration	xii
Abstract	xiii

Table of Contents

CHAPTER 1: INTRODUCTION	1
1.1 Background of the study	1
1.2 Bank financial strength ratings and bank capital structure	3
1.3 The main research summary	3
1.3.1 Research problem	4
1.3.2 Research objectives	5
1.3.3 Research questions	7
1.3.4 Research hypotheses	8
1.3.5 Contribution of this research to the existing literature	10
1.4 The structure of the thesis	12
CHAPTER 2: A REVIEW OF RELEVANT LITERATURE	14
2.1 Introduction	14
2.2 Rating definition and purpose	14
2.2.1 Rating definition	14
2.2.2 Rating purpose	15
2.2.3 Rating agencies' mechanism	16
2.2.4 Solicited vs. unsolicited	18
2.3 The methodology of bank rating	23
2.3.1 CAMEL approach	25
2.3.1.1 Capital adequacy	25

2.3.1.2 Asset quality 26
2.3.1.3 Earnings 26
2.3.1.4 Management quality 27
2.3.1.5 Liquidity 27
2.3.2 Capital Intelligence bank rating methodology 28
2.4 Bank rating and bank capital structure 29
2.4.1 Principal-agent relationship 32
2.4.2 Basel I and II 34
2.4.3 Bank CS and financial variables 39
2.5 Bank ratings: Empirical findings 42
2.6 Financial sector in the Middle East region 50
2.6.1 Banking industry in developing versus developed economies 52
2.6.2 Banking sector in the Middle East region 53
2.7 Rating agencies 54
2.7.1 Standard & Poor's 54
2.7.2 Moody's 56
2.7.3 Fitch 58
2.7.4 Capital Intelligence (CI) 61
2.8 Conclusion 68

CHAPTER 3: METHODOLOGY AND DATA COLLECTION 69
3.1 Introduction 69
3.2 Data and research methods 70
3.2.1 Data collection 70
3.2.2 Dependent variable 72
3.2.3 Independent variables 73
3.2.4 Control variables 79
3.3 Statistical estimation models 81
3.3.1 Multicollinearity 81
3.3.2 Multinomial logit (ML) model 82
3.3.3 The process of choosing statistical predictive techniques 85
3.3.3.1 Evaluation criteria 87
3.3.3.1.1 Average correct classification criterion 87

3.3.3.1.2 Estimated misclassification cost criterion 88
3.3.3.1.3 Gains chart 89

3.3.4 CHAID 90

3.3.5 CART 92

3.3.6 Neural networks 95

3.3.6.1 Neural network fundamentals 97

3.3.6.2 The structure of neural networks 98

3.3.6.3 Multilayer perceptron 100

3.3.7 Discriminant function 102

3.3.7.1 Discriminant analysis (Z-score model) 103

3.3.7.2 Discriminant, content and construct validity 104

3.3.8 Logistic regression 105

3.4 Conclusion 107

CHAPTER 4: MULTINOMIAL LOGIT (ML) RESULTS 109

4.1 Introduction 109

4.2 Descriptive statistics 109

4.3 ML results 110

4.3.1 Asset quality models 111

4.3.2 Capital adequacy models 120

4.3.3 Credit risk models 127

4.3.4 Liquidity models 135

4.3.5 Profitability models 143

4.3.6 All financial category models 154

4.4 Conclusion 166

CHAPTER 5: PREDECTIVE TECHNIQUES RESULTS 168

5.1 Introduction 168

5.2 CHAID 169

5.2.1 Entire data set 169

5.2.2 Subsample$_1$: 67% training subsample and 33% testing subsample 170

5.2.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample 171

5.3 CART 173

5.3.1 Entire data set 173

5.3.2 Subsample$_1$: 67% training subsample and 33% testing subsample 174

5.3.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample 176

5.4 Multilayer perceptron neural networks 178

5.4.1 Entire data set 178

5.4.2 Subsample$_1$: 67% training subsample and 33% testing subsample 179

5.4.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample 180

5.5 Discriminant analysis 182

5.5.1 Entire data set 182

5.5.1.1 Relative contribution of the model's discriminatory power 188

5.5.1.2 Classification matrix of discriminant analysis using entire data set 189

5.5.2 Subsample$_1$: 67% training subsample and 33% testing subsample 190

5.5.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample 191

5.6 Logistic regression 193

5.6.1 Entire data set 193

5.6.2 Subsample$_1$: 67% training subsample and 33% testing subsample 194

5.6.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample 196

5.7 Comparison of results of various bank FSR group membership models 198

5.8 Conclusion 202

CHAPTER 6: CONCLUSION 204

6.1 Introduction 204

6.2 Summary of research findings 207

6.2.1 Summary of ML findings 207

6.2.1.1 Bank performance financial categories 207

6.2.1.2 All financial categories 214

6.2.1.2.1 Financial variables 214

6.2.1.2.2 Nonfinancial variables 214

6.2.2 Summary of bank FSR group membership results 215

6.3 Policy implications 217

6.4 Research limitations 218

6.5 Recommendations for future research 218

REFERENCES 220

Appendices

Appendix A: Summary of the relevant studies in the literature 241

Appendix B: Descriptive statistics for dependent and explanatory variables for low- and near-low FSRs 258

Appendix C: Descriptive statistics for dependent and explanatory variables for high- and near-high FSRs 262

Appendix D: Descriptive statistics for dependent and explanatory variables for all FSRs 266

Appendix E: Analysis of model-fitting criteria and likelihood ratio tests for logistic regression model 270

List of Figures

Chapter 2

Figure 2.1 CI's rating process 28

Chapter 3

Figure 3.1: Flow chart diagram of the ML model 85

Figure 3.2: An evaluation chart for the five predictive statistical techniques 87

Figure 3.3: Basic neuron model 99

Figure 3.4: MLP feed-forward architecture (one hidden layer) 101

Chapter 5

Figure 5.1: Gains charts for testing subsample$_1$ and testing subsample$_2$ using CHAID 173

Figure 5.2: Gains charts for testing subsample$_1$ and testing subsample$_2$ using CART 177

Figure 5.3: Gains charts for testing subsample$_1$ and testing subsample$_2$ using MLP neural network 182

Figure 5.4: Histograms showing the distribution of discriminant scores for low- and high-FSR group memberships 186

Figure 5.5: Gains charts for testing subsample$_1$ and testing subsample$_2$ using discriminant analysis 193

Figure 5.6: Gains charts for testing subsample$_1$ and testing subsample$_2$ using LR 198

List of Tables

Chapter 2

Table 2.1: Endogenous relationship between bank CS and financial variables 39

Table 2.2: Long-term ratings/scales for the four rating agencies 62

Table 2.3: Short-term ratings/scales for the four rating agencies 65

Chapter 3

Table 3.1: Descriptive statistics for banks, by country and whether rated by CI, based on bank size (in total assets) 71

Table 3.2: A synopsis of CI bank FSRs, numerical ratings and rating categories 73

Table 3.3: List of the bank financial variables examined in this thesis 74

Table 3.4: Classification matrix 88

Chapter 4

Table 4.1: Asset quality results for ML model with and without bank FSR dummies 111

Table 4.2: Parameter estimates for the asset quality model without dummies (Model 1) 114

Table 4.3: Parameter estimates for the asset quality model with dummies (Model 2) 114

Table 4.4: Capital adequacy results for ML model with and without bank FSR dummies 120

Table 4.5: Parameter estimates for the capital adequacy model without dummies (Model 1) 122

Table 4.6: Parameter estimates for the capital adequacy model with dummies (Model 2) 123

Table 4.7: Credit risk results for ML model with and without bank FSR dummies 127

Table 4.8: Parameter estimates for the credit risk model without dummies (Model 1) 130

Table 4.9: Parameter estimates for the credit risk model with dummies (Model 2) 130

Table 4.10: Liquidity results for ML models with and without bank FSR dummies 135

Table 4.11: Parameter estimates for the liquidity model without dummies (Model 1) 138

Table 4.12: Parameter estimates for the liquidity model with dummies (Model 2) 138

Table 4.13: Profitability results for ML model with and without bank FSR dummies 143

Table 4.14: Parameter estimates for the profitability model without dummies (Model 1) 146

Table 4.15: Parameter estimates for the profitability model with dummies (Model 2) 147

Table 4.16: Results for financial categories for ML model with and without bank FSR dummies 154

Table 4.17: Parameter estimates for all financial categories' model without dummies (Model 1) 157

Table 4.18: Parameter estimates for all financial categories’ model with dummies (Model 2) 158

Chapter 5

Table 5.1: Classification results for CHAID using entire data set 169
Table 5.2: Classification results for CHAID using training $subsample_1$ 170
Table 5.3: Classification results for CHAID using testing $subsample_1$ 170
Table 5.4: Classification results for CHAID using training $subsample_2$ 171
Table 5.5: Classification results for CHAID using testing $subsample_2$ 171
Table 5.6: Classification results for CART using entire data set 174
Table 5.7: Classification results for CART using training $subsample_1$ 174
Table 5.8: Classification results for CART using testing $subsample_1$ 175
Table 5.9: Classification results for CART using training $subsample_2$ 176
Table 5.10: Classification results for CART using testing $subsample_2$ 176
Table 5.11: Classification results for MLP neural network using entire data set 178
Table 5.12: Classification results for MLP neural network using training $subsample_1$ 179
Table 5.13: Classification results for MLP neural network using testing $subsample_1$ 179
Table 5.14: Classification results for MLP neural network using training $subsample_2$ 180
Table 5.15: Classification results for MLP neural network using testing $subsample_2$ 181
Table 5.16: The components of the discriminant model for low- and high-FSR group membership 184
Table 5.17: The cut-off point for the low- versus high-FSR group membership 187
Table 5.18: Relative contribution of the models’ discriminatory power 188
Table 5.19: Classification results for discriminant analysis using entire data set 189
Table 5.20: Classification results for discriminant analysis using training $subsample_1$ 190
Table 5.21: Classification results for discriminant analysis using testing $subsample_1$ 191
Table 5.22: Classification results for the discriminant analysis using training $subsample_2$ 191
Table 5.23: Classification results for discriminant analysis using testing $subsample_2$ 192
Table 5.24: Classification results for LR using entire data set 194
Table 5.25: Classification results for LR using training $subsample_1$ 195
Table 5.26: Classification results for LR using testing $subsample_1$ 195
Table 5.27: Classification results for LR using training $subsample_2$ 196
Table 5.28: Classification results for LR using testing $subsample_2$ 197

Table 5.29: Comparing classification results for various techniques 199
Table 5.30: Errors and estimated misclassification costs for all proposed models 200

List of Abbreviations

Abbreviation	Full word
ACC	Average Correct Classification rate
BFSR	Bank Financial Strength Rating issued by Moody's
BIS	Bank of International Settlements
BCBS	Basel Committee on Banking Supervision
CART	Classification and Regression Trees
CHAID	Chi-squared Automatic Interaction Detector
CI	Capital Intelligence
CS	Capital Structure
EMC	Estimated Misclassification Cost
DA	Discriminant Analysis
FSRs	Financial Strength Ratings issued by Capital Intelligence
FBR	Bank Individual Rating issued by Fitch
GCC	Gulf Cooperation Council
IRB	Internal Ratings-Based approach
LR	Logistic Regression
LTR	Long-Term Rating issued by S&P
ML	Multinomial Logit
MLP	Multilayer Perceptron
NRSROs	Nationally Recognised Statistical Ratings Organisations
RAs	Rating Agencies
SR	CI national long-term credit rating (i.e., country sovereign ratings)
SEC	U.S. Securities and Exchange Commission
VIF	Variance Inflation Factor

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Author's Declaration

The author has not been registered for any other University award during the registration period for the degree of Doctoral of Philosophy without prior approval from supervisors.

The following activities have been undertaken during the PhD registration period at Salford Business School:

I. Attended Doctoral training programme in:
- Preparing for Interim and Internal Evaluations
- Introduction to Quantitative Research Methods
- PhD Research Methodology – Lessons from Sociology
- Data Analysis – Quantitative Data Collection
- Introduction to SPSS.

II. Doctoral publication related to PhD topic
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List of international refereed conferences

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- 'The Effect of Bank Capital Structure and Financial Indicators on CI's Financial Strength Ratings: The Case of The Middle East' *2nd World Finance Conference,* Rhodes, Greece, 15- 17 June 2011.

IV. Selected publications in international referred journals, including:
- Eldomiaty, T., Ismail, M.A. and Mostafa, W. (2012) 'Testing A Potential Signaling of Capital Structure Decisions in Transitional Market: Subset Model Selection Approach', *Advances in Quantitative Analysis of Finance and Accounting*, 10 (1), pp. 255-283.
- Eldomiaty, T., Charara, S. and Mostafa, W. (2011) 'Monitoring the Systematic and Unsystematic Risk in Dubai General Index Do Financial Fundamentals Help?', *Journal of Emerging Market Finance*, 10(3), pp. 285-310.

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Abstract

The relationship between bank performance measures, namely financial and nonfinancial, and financial strength ratings (FSRs) has created an interesting area of research for many years. This thesis examines econometric qualities including explanatory, discriminatory and predictive powers. The main aims of this thesis are as follows: (1) to identify the main bank performance measures associated with high-FSRs versus low-FSRs; (2) to determine the bank performance measures that can discriminate banks associated with high-FSRs versus low-FSRs; and (3) to compare the predictive capabilities of conventional techniques versus machine-learning techniques in predicting banks' FSR group memberships in the Middle East.

The analysis is performed in three stages: (1) the analysis identifies the association between banks' FSRs and performance measures by applying a multinomial logit technique; (2) the analysis uses the outcome of the first stage as an input to discriminate high-FSRs from low-FSRs using discriminant analysis; and (3) machine-learning techniques (i.e., CHAID, CART and multilayer perceptron neural networks) and conventional techniques (i.e., discriminant analysis and logistic regression) are used to predict banks' FSR group memberships. Various performance evaluation criteria (i.e., average correct classification rate, misclassification cost and gains charts) are used to evaluate the predictive capabilities of various modeling techniques. The data set covers the Middle Eastern countries' commercial banks from 2001 to 2009.

Results from the first stage indicate that high-FSR banks in the Middle East are well capitalised, and profitability is associated with the highest relative explanatory power. Second stage results show that three financial variables (i.e., loan loss provision to total loans ratio, asset utilisation ratio and equity to net loans ratio) contribute greatly to the model's discriminatory power. On the other hand, results for nonfinancial variables reveal that bank size and sovereign rating are the most important to the model's discriminatory power. The results indicate that financial variables outperform nonfinancial variables in terms of overall discriminatory power. Finally, in the last stage, results show that the predictive capability of CHAID outperforms other machine-learning techniques (i.e., CART and multilayer perceptron neural networks). Regarding conventional techniques, the predictive capability of discriminant analysis is superior to logistic regression. In terms of comparing various predictive techniques, results of the performance evaluation criteria reveal that machine-learning techniques outperform conventional techniques in predicting banks' FSR group memberships.

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The relationships between bank performance measures (i.e., financial and nonfinancial) and banks' Financial Strength Ratings (FSRs) provide insights into the significance of bank activities. The reason is that bank rating is conducted by external rating agencies (RAs) that use usually opaque and unpublished methods to assign a rating based on banks' financial and nonfinancial measures. Singleton and Surkan (1991) stated that most practitioners and academe face problems with RAs such as Standard and Poor's (S&Ps) and Moody's concerning the dearth of specific public knowledge on how rating classification decisions are made. A lack of consensus is observed regarding the ability of RAs to assign correct bank ratings (Altman and Rijken, 2004; Altman and Saunders, 1997; Amato and Furfine, 2004; Chen, 2012). In addition, RAs face difficulties in developing an accurate credit rating system for banks because of the opacity of and leverage across financial institutions. This is supported by the fact the three major RAs (i.e., Moody's, Standard & Poor's and Fitch) disagree more strongly when issuing bank ratings than when issuing corporate and country ratings (Cantor and Packer, 1994; Hammer et al., 2012; Moon and Stotsky, 1993; Morgan, 2002).

It is worth noting that the three major private rating agencies were liable for the housing bubble and consequently financial crash of 2007-08 (Bussani, 2010; Diomande et al., 2009). Along with the Asian financial crisis, the two above-mentioned crises have highlighted massive problems in the banking systems and that correct ratings of banks' FSRs tends to be more important than ever. The reform of the rating industry became crucial especially after 2007-2008 financial crisis and the European sovereign-debt crisis. This is a result of the fact that most RAs failed to foresee default events and the downgrades of corporations, sovereign governments and banks (Laere et al., 2012; Sy, 2009). Thus, the need to develop an accurate internal bank rating model to overwhelm the whims of RAs is crucial.

In terms of bankruptcy, a major difference exists between bank and non-bank firms. The bankruptcy of a large non-banking firm has relatively lesser impact on the whole economy than the collapse of a bank. Bank failure results in a systemic crisis that negatively affects the economy at large (e.g., Latin America, Asia and the US housing bubble crisis). This is mainly because bank failures inversely affect investors' confidence in the financial system and decrease credit supply, which in turn results in economic recession. Additionally, the banking business depends to a great extent on public confidence, which helps banks to attract financial resources (i.e., deposits) and invest those resources in profitable opportunities.

In the present economy, bank ratings have become essential especially after the recent financial turmoil. Bank ratings are ordinal measures that send signals to market participants about the banks' current and future financial positions as well as the bank's default probability. Bank FSRs are considered an important indicator for investors, depositors, debtors and regulators in assessing the bank's financial strength (Pasiouras et al., 2007). In emerging economies, banks' financial strength plays a vital role because of relative deficiencies in the financial markets; opaque banking sectors; and inadequate regulatory, institutional and legal environments (Godlewski, 2007). In addition, a strong bank FSR assists banks to access capital markets in better conditions and positively affects bank operations and performance. De Ceuster and Masschelein (2003) supported the notion that 'the credit ratings of banks provide important bits of information and hence directly serve as an instrument of market discipline' (p.757). In this case, public confidence is expected to improve if the financial and nonfinancial measures associated with high FSRs are disclosed. This is one of the main objectives of this thesis.

1.2 Bank financial strength ratings and bank capital structure

The relevant literature on bank FSRs includes an intermediary factor that is bank capital structure (CS), namely, equity as a proportion of total assets. The reason for the involvement of bank CS is that it affects bank FSRs given that the adjustment of capital structure is largely controlled by universal bank supervisory regulations (e.g., Basel I, II and III). Estrella (2000) investigated the importance of capital ratios in predicting US bank failures and found a strong association between capital ratios and S&P debt ratings. Shen et al. (2012) provided further support for this view and suggested that RAs treat bank capital considerably differently from other financial ratios. The authors concluded that bank capital is a crucial determinant of bank rating, as it guards against bank default even in countries with low information asymmetry.

Therefore, as the sources of bank capital are regulated, bank FSRs are implicitly regulated. This requires bank managers to design financial strategies that do not deviate from regulations and support banks obtaining high FSRs. The above-mentioned argument, among others, calls for the involvement of bank CS as one of the determinants of bank FSRs assigned by Capital Intelligence (CI).

1.3 The main research summary

The purpose of this thesis is to identify the influence of bank CS and bank financial and nonfinancial measures on bank FSRs assigned by CI in the Middle East region using multinomial logit (ML) technique. In addition, this thesis determines the main financial and nonfinancial measures that discriminate between high-FSR and low-FSR banks using discriminant analysis (DA) technique.

This is followed by an evaluation of various statistical predictive techniques to predict banks' FSR group memberships. This is done by applying both machine-learning techniques (e.g., chi-squared automatic interaction detector [CHAID], classification and regression trees

[CART] and multi-layer perceptron [MLP] neural networks), as well as conventional techniques (e.g., DA and logistic regression [LR]). This section provides a discussion of the research problem, research objectives, research questions and research contribution.

1.3.1 Research problem

The literature on the determinants and prediction of bank FSRs is extensive and well-established for developed economies (Belloti et al., 2011a; Hammer et al., 2012; Öğüt et al., 2012; Pasiouras et al., 2006; Poon et al., 1999; Poon and Firth, 2005) . In terms of bank FSRs, the Middle East region is not as well recognised in the literature as developed countries. This is mainly because of four main problems that have evolved over time.

Firstly, Middle Eastern banks' equity financing has been obtained mainly from governments. Secondly, because most Middle East banks are government banks, there has been less need to assess banks' creditworthiness (Harington, 1997). Governments are using their banks to finance their economic activities to an extent that has caused a disconnection between bank FSR and bank CS. Thirdly, the market forces that monitor capital risk have been absent because the stock markets have been underdeveloped or even non-existent in many Middle East countries. Consequently, there has been less interest in bank FSRs (only 47.4% of commercial banks—64 out of 135—are rated)[1]. Fourthly, the opening and development of various stock markets in the region have encouraged many foreign banks to establish themselves there. This has stimulated the mostly unrated Middle Eastern banks to make their performance comparable to that of the rated foreign banks.

[1] According to Bank scope database as of 27 January 2011

1.3.2 Research objectives

The objectives of this thesis are derived from the above-mentioned research problems. The objectives reflect the orientation of this thesis, which focuses on the mutual relationships between banks' CS, financial and nonfinancial measures and bank FSRs. Accordingly, the objectives are outlined as follows:

(1) Examine the impact of bank CS decisions on bank FSR. This possible impact has its deep roots in Bank for International Settlements (BIS) universal regulations known as Basel I, II, and III. These regulations have a universal objective, which is to protect bank capital using classified guidance for bank asset quality, capital adequacy, credit risk, liquidity and profitability.

(2) Investigate the association between bank FSR and bank performance in terms of financial and nonfinancial measures. The objective is to determine the main financial and nonfinancial measures associated with high- and near-high FSRs versus low- and near-low FSRs of active commercial banks operating in the Middle East.

(3) Examine how financial and nonfinancial measures affect high- versus low-FSR in the Middle East. The main objective is to determine the main financial and nonfinancial measures that can discriminate between banks associated with high- versus low-FSRs. Each RA has its own customised rating system, the details of which are not published. Practitioners as well as researchers can benefit from this thesis as it helps in the design and adjustment of bank financial strategies in the Middle East to achieve high FSRs.

(4) Examine the relative explanatory power of financial versus nonfinancial measures for bank FSRs in the Middle East.

(5) Examine the usefulness of conventional as well as machine-learning statistical predictive techniques for predicting banks' FSR group memberships in the Middle East.

It is noteworthy that this thesis differs from other related studies in various terms as follows:

- The researcher examines bank FSR assigned by CI, in contrast to other studies that have investigated bank individual ratings (FBR) and bank financial strength ratings (BFSR) assigned by Fitch and Moody's, respectively.[2] CI is more specialised in rating banks in the Middle East region than the other two rating agencies. According to Bank scope database as of 27 January 2011, *the cut-off date in this research for the collection of data for subsequent analysis,* CI assigns bank FSRs for 64 commercial banks in the Middle East whereas Fitch and Moody's issue FBR[3] and BFSR for only 50 and 48 commercial banks in the same region, respectively.
- The researcher is using a relatively comprehensive sample in terms of time coverage, number of banks and current bank FSRs.
- To the best of researcher's knowledge, no other studies have investigated which financial and nonfinancial measures are associated with high- and near-high FSR banks in the Middle East region.
- The researcher is not aware of other studies in the Middle East region that have addressed the use of conventional and machine-learning techniques in predicting

[2] S&P has no publicly available equivalent to these ratings.
[3] Fitch bank individual rating has been recently withdrawn in favour of the so-called Viability Rating, which express the same risk levels as Fitch bank individual rating but with greater granularity.

banks' FSR group memberships. Thus, the aim is to close this gap in the Middle Eastern banking sector.

1.3.3 Research questions

According to the above-mentioned research objectives, this thesis examines the questions that follow:

(1) Does bank CS matter in the determination of high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(2) Does bank asset quality matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(3) Does bank capital adequacy matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(4) Does bank credit risk matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(5) Does bank liquidity matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(6) Does bank profitability matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(7) Does country sovereign rating matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(8) Does bank size matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(9) Does country effect matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(10) Does time effect matter to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(11) Are bank overall financial and nonfinancial measures significant to high- and near-high FSRs versus low- and near-low FSRs of commercial banks in the Middle East region?

(12) Are financial or nonfinancial measures more significant to Middle Eastern banks' FSRs?

(13) How can bank financial and nonfinancial measures be used to differentiate between banks associated with high FSRs versus low FSRs?

(14) How can bank financial and nonfinancial measures be used to predict banks' FSR group memberships by employing different statistical predictive techniques?

1.3.4 Research hypotheses

The above-mentioned research questions were the basis for the development of the following hypotheses:

H_{A1}: A positive association exists between bank CS and the level of FSRs [4].

H_{A2}: A negative association exists between bank asset quality and the level of FSRs.

H_{A3}: A positive association exists between bank capital adequacy and the level of FSRs.

[4] Clearly, the null hypothesis (H_{01}) expresses no relationship exists between bank CS and the level of FSRs and null hypotheses corresponding to the subsequent hypotheses can be derived similarly.

H_{A4}: A negative association exists between bank credit risk and the level of FSRs**.**

H_{A5}: A positive association exists between bank liquidity and the level of FSRs.

H_{A6}: A positive association exists between bank profitability and the level of FSRs.

H_{A7}: A positive association exists between country sovereign ratings and the level of FSRs.

H_{A8}: A positive association exists between bank size and the level of FSRs.

H_{A9}: A positive association exists between country effect and the level of FSRs.

H_{A10}: A positive association exists between time effect and the level of FSRs[5].

H_{A11}: All financial and nonfinancial measures are associated with higher explanatory power than individual bank categories.

H_{A12}: Financial measures are associated with higher explanatory power than nonfinancial measures.

H_{A13}: Financial measures are associated with higher discriminatory power than nonfinancial measures.

H_{A14}: In terms of banks' FSR group memberships prediction, sophisticated machine-learning techniques outperform conventional techniques.

[5] This hypothesis requires particular formulation as far as banks should be concerned with improving FSR through time (DeSerpa, 1971).

1.3.5 Contribution of this research to the existing literature

The contribution of this thesis can be outlined as follows.

(1) This thesis discusses the association between bank CS and bank FSR in the Middle East. To the best of the researcher's knowledge, recognisable current and relevant research on this topic has addressed the relationship between credit rating and capital structure using data mainly from US and other developed countries (Graham and Harvey, 2001; Kisgen, 2006; Shivdasani and Zenner, 2005). The findings of this thesis in the Middle East may deepen the understanding of the relationship between bank CS and bank FSRs in different regions.

(2) The researcher examines financial as well as nonfinancial measures that may have an effect on bank FSR in the Middle East. The contribution is that both types of data address the extent to which public data provide reasonable and adequate explanatory power for bank FSR in the Middle East. This argument is based on inherent academic claims that a lack of consensus is observed regarding the basis upon which bank FSR is assigned by private RAs (Bussani, 2010; Diomande et al., 2009). Therefore, the method used in this thesis validates bank FSRs issued by RAs in the Middle East region.

(3) The method adopted by RAs to produce bank FSRs does not reveal how financial and nonfinancial measures are used.[6] The method offered in this thesis provides systematic and practical approach to the assignment of banks in the Middle East of

[6] In a personal communication (29 March 2010) between the researcher and Capital Intelligence, Capital Intelligence confirmed that the basis of assigning a certain FSR to a bank is neither revealed to the bank nor to the public.

high- and near-high FSRs versus banks with low- and near-low FSRs. This perspective is quite different from other relevant studies as it provides an answer to the following question: *Why does a bank FSR matter?* This thesis offers significant contribution to the bank rating literature for the Middle East from both a policy and an academic perspective in terms of formulating banking strategies that promote high- and near-high FSRs.

(4) The contribution of this thesis also addresses the possible association between bank activities (asset quality, capital adequacy, credit risk, profitability and liquidity) and bank FSRs in the Middle East. The reason is that bank financial strategies are primarily formulated on an individual basis at different departments and then aggregated at the end of the financial period. It is necessary to show how each bank activity provides a contribution to the overall bank FSR. The researcher shows the relative contribution of each bank activity to the formulation of effective bank strategies by examining the individual role of each activity as well as the aggregate role in relation to different levels of bank FSR.

(5) This thesis contributes to the current and relevant literature in that it examines all of the econometric qualities of the models commonly discussed in literature. These qualities include the explanatory, discriminatory and the predictive powers of the models. This thesis applies wide range of statistical techniques to predict banks' FSR group memberships in the Middle East. These techniques include conventional methods (i.e., DA and LR) as well as machine-learning techniques, (i.e., CHAID, CART and MLP neural networks). The modelling of predictive banks' FSR group memberships helps bank managers to understand the intrinsic process used by CI's analysts.

1.4 The structure of the thesis

This thesis is divided into six chapters. The first chapter introduces the thesis. The second chapter starts with a review of the rating definition, purpose and its relative importance to the economy and distinguishes between solicited and unsolicited ratings. Chapter two continues by explaining in detail the methodology of bank rating as practiced by RAs with a special focus on CI bank rating methodology. This is followed by a review of related studies that have investigated the determinants of bank ratings. This chapter concludes by introducing relevant knowledge about the performance of the financial sector, especially the banking sector, in the Middle East region as well as an overview of the main activities and rating scale definition for major RAs in the world.

The third chapter discusses the research methods used in this thesis in terms of the data (classified into four quartiles according to FSR: high, near-high, low and near-low). The chapter also provides a detailed explanation of the financial and nonfinancial measures used in this thesis. This chapter concludes with a review of the various statistical methods that are employed in the analysis.

Chapters four and five are the focus of this thesis. Chapter four presents the results of the multinomial logit (ML) for the five main bank performance categories (asset quality, capital adequacy, credit risk, liquidity and profitability) as well as the overall category that includes the above-mentioned five categories. In each category, the regression results are divided into two parts: the first regression model reports results without the inclusion of nonfinancial measures and the second regression model reports the results after the addition of nonfinancial measures to the regression model.

Chapter five reports a wide range of banks' FSR group memberships predictive models' classification rates, misclassification costs and gains charts results of various statistical predictive techniques (conventional and machine-learning) using the entire data set and two different subsamples. In addition, chapter five provides the results of the DA, including the main financial and nonfinancial measures that can be used to discriminate between banks with high- versus low-FSRs in the Middle East region. Chapter six concludes by pinpointing the main findings of this thesis and suggests some policy implications that may be useful for bank management and policymakers in the Middle East region.

CHAPTER 2: A REVIEW OF RELEVANT LITERATURE

2.1 Introduction

This chapter reviews the literature on bank FSR and is organised as follows. Section 2.2 starts by explaining the ratings definition, purpose and the RAs' mechanism. This is followed by a review of the differences between solicited and unsolicited ratings. Section 2.3 discusses the methodology of bank rating as practiced by RAs with particular focus on CI's bank rating methodology. Section 2.4 discusses the relationship between a bank's rating and its capital structure. Section 2.5 reviews the relevant literature about bank rating and its determinants. Section 2.6 introduces relevant knowledge about the financial sector, especially the banking sector, in the Middle East region. Section 2.7 reviews the most common RAs in terms of the meaning of rating scales used by every rating agency. Finally, section 2.8 concludes this chapter.

2.2 Rating definition and purpose

This section introduces the definition of rating as per different RAs, discusses the purpose of the rating, highlights the mechanism adopted by RAs and finally distinguishes between solicited and unsolicited ratings.

2.2.1 Rating definition

John Moody issued the first publicly available railroad bond ratings to bond investors in 1909. This was followed by Moody's firm and Poor's Publishing Company in 1916, the Standard Statistics company in 1922, and the Fitch Publishing company in 1924 (White, 2010). According to Moody's Investor's Service (2012), rating is defined as 'the purpose of Moody's ratings is to provide investors with a simple system of gradation by which future relative creditworthiness of securities may be gauged.' (para.1). Similarly, Standard & Poor's (2012a) defines rating as '…agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time.' (para.1). Also, Fitch (2013) defines rating as

> '. . .an opinion on the relative ability of an entity to meet financial commitments, such as interest, preferred dividends, repayment of principal, insurance claims or counterparty obligations. Credit ratings are used by investors as indications of the likelihood of receiving the money owed to them in accordance with the terms on which they invested.'(p.6)

In addition, CI (2011) defines rating as '…the general creditworthiness of an entity (sovereign, bank or corporate) and the likelihood that it will meet its financial obligations in a timely manner.' (para. 1)

In the light of these definitions, *rating* is a multidimensional, forward-looking process that generates signals and indicators used to assess the creditworthiness of borrowers and to minimise default rates (Boot et al., 2006; Cantor and Packer, 1994). Financial intermediaries (banks and non-banking institutions) are key players in this area. RAs gather, analyse and process information to produce some rating indices. These indices guide investors in differentiating between good and bad borrowers.

2.2.2 Rating purpose

The rating process—whether sovereigns, banks or corporate—does not constitute a recommendation to purchase, sell or hold a particular security. It neither points out any investment opportunity that is suitable for a particular investor nor is it used as an audit or control of the company's finances. RAs stress that their ratings constitute opinions (Fight, 2001). However, sometimes the high fees of RAs may be justified in terms of facilitating easy access to capital markets, building international market reputation, lowering costs of borrowing and providing issuers with great financial flexibility.

From investors' points of view, ratings reduce uncertainty, which in turn promotes market growth and enhances efficiency and liquidity. Boot et al. (2006) stated, 'Rating agencies could be seen as information-processing agencies that may speed up the dissemination of information to financial markets' (p. 84). It is obvious that RAs have, or must have, a significant role mitigating the agency problem, thus reducing the associated agency costs. That is, RAs reduce uncertainty to guide investors to select benchmark investments with manageable risks and limit agency costs[7]. For example, credit-rating restrictions can be written into the mandate for the management of large public fund, restricting investment in speculative grade securities. For this reason, most companies and international debt issuers ask for a rating from one of the nationally recognised statistical ratings organisations (NRSROs)[8].

From RAs' points of view, high costs may be required to conduct dependable quantitative analysis (e.g., ratio analysis, cash flow analysis, macroeconomic variables, sovereign risk, and industry analysis) as well as accurate qualitative analysis (e.g., assessment of financial strength, management performance and corporate governance). Perhaps differences between agencies in this regard explain why few of them have gained international reputations.

2.2.3 Rating agencies' mechanism

RAs are privately owned; operate without government mandate; are independent from the investment community and expert in the process of issuing ratings and debt instruments. The

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[7] Agency theory is a concept that explains the relationship between principals, namely shareholders, and agents of the principals, namely company executives. The agency theory addresses two agency problems to deal with: (1) the conflict of interest between principal and agent (2) the difference of risk attitudes between principal and agent. Agency costs arise from agency problems that are borne by shareholders and represent a loss of shareholder wealth (Milgrom and Roberts, 1992).

[8] NRSRO include list of RAs that are authorized by the U.S. Securities and Exchange Commission (SEC) to issue ratings for certain regulatory purpose. The RAs designated as NRSROs are as follows: Standard & Poor's Ratings Services, Moody's Investors Services, Fitch Ratings, Kroll Bond Rating Agency, A.M. Best Company, Dominion Bond Rating Service, Ltd, Japan Credit Rating Agency, Ltd, Egan-Jones Rating Company, Morningstar, Inc., and HR Ratings.

world of rating consists of about 150 RAs operating worldwide. Moody's Investor Service and Standard & Poor's, which control about 80% of the market, dominate the industry worldwide. They have a designation from the NRSRO apart from their sustained creditability; they have revealed personnel and know-how advantages. CI is another example of a well-known international agency that specialises in analysing banks in emerging markets. Development and history, shareholding structure, analyst recruitment policies and qualifications and the marketing of services and publications differ across agencies.

It is noteworthy that a conflict of interest has automatically arisen in the rating industry as a result of the transition from charging investors to charging issuers. This is supported by the fact that 90% of Moody's and Fitch's revenues come from fees paid by the issuers (U.S. Securities and Exchange Commission, 2003). Thus, certified RAs have more interest in helping issuers benefit from a favoured regulatory treatment rather than providing valuable and accurate information to investors. Weber and Darbellay (2008) argued that certified RAs may favour issuers at the expense of investors to benefit from a favoured regulatory approach. In this regard, the accessible information for investors may be inaccurate. In the same context, it has been argued that certified RAs no longer care about their reputation relative to the generation of valuable information to investors as a consequence of the ratings-dependent regulation. This normally articulates the failure of RAs in announcing an issuer's downgrade and in issuing inflated ratings. Therefore, it is perceived that RAs are not in a position to anticipate financial crisis.

The global financial system experienced a severe financial crisis in 2007-2008. Consequently, this led to the bankruptcy of many banks in the United States and Europe; of those that did not fail, many banks were either taken over or rescued by their governments. In spite of the fact that the 2007-2008 financial crisis originated from the subprime lending of the housing market, its effect extends across various segments of the credit market. The 2007-2008 financial crisis' impact on major commercial banks is supported by the fact that Citigroup, one of the largest commercial banks, between the second quarter of 2007 and October 2008, shrank from $255 bn to $82 bn (Liu and Mello, 2008). The financial crisis and the European sovereign-debt crisis assist practitioners and researchers to pinpoint the main problems that face RAs, such as conflict of interest, failure to rate derivatives, lack of accountability, barriers to entry in the rating industry (lack of competition) and vague and questionable rating methods (Bolton et al., 2012; Laere et al., 2012; Sy, 2009; White, 2010).

2.2.4 Solicited vs. unsolicited

As mentioned earlier, the working and functioning environment of RAs have drawn considerable public attention for several reasons: (1) RAs failed to predict the 1997 Asian crisis and many other corporate scandals such as Enron (2001), WorldCom, Inc. (2002) and Lehman Brothers (2008) as well as the 2007-2008 financial crises and European sovereign-debt rating; (2) RAs play a vital role in the regulatory mechanism of financial markets; and (3) doubts concerning the transparency and reliability of the rating process, especially the practice of unsolicited rating. *Unsolicited rating* is the rating conducted by RAs without a formal permission from the issuer.

The first issue of unsolicited ratings was made by Moody's in 1909. *Public information rating* and *shadow ratings* are softer terms used by RAs (S&P and Fitch, respectively) for unsolicited ratings. Moody's has a policy of not distinguishing between solicited and unsolicited ratings and thus initiated a statement that accompanies the assignment of unsolicited ratings: '*This rating was initiated by Moody's. The issuer did not participate in the assignment processes*'. CI also assigns ratings on an unsolicited basis based on public information; these ratings are formatted in lowercase letters (i.e., bbb+ or a-).

According to Baker and Mansi (2002), unsolicited ratings result in a conflict among issuers, investors, RAs and regulators alike. Such conflict stems from the fact that unsolicited ratings tend to be lower than solicited ratings (Poon, 2003; Van-Roy, 2006). It has been argued that some banks consider Moody's practice of assigning unsolicited ratings as blackmail (Harington, 1997). Among others, Moon and Stotsky (1993), Cantor and Packer (1997) and Pottier and Sommer (1999) stressed that controlling for self-selection bias, rating determinants and their importance as well as rating scales differ significantly across RAs. For unsolicited ratings, the reason for this perceived downward bias is either to persuade issuers to pay for higher solicited ratings or the absence of formal, in-depth meetings between RAs and the issuer's management. These meetings provide RAs with inside (i.e., private) information about the entity being rated that may not have been disclosed in its published annual reports (Golin, 2001). In line with this, Baker and Mansi (2002) stated that unsolicited ratings are less accurate than solicited ones because of the absence of inside information. Thus, private information plays a crucial role in determining accurate ratings to be assigned by RAs.

On the other hand, RAs defend unsolicited ratings as being of great importance to investors and market participants who request ratings for institutions that are unwilling to participate in the rating process or pay the rating fees. Moreover, RAs have argued that unsolicited ratings increase competition among RAs and that unsolicited ratings prevent firms from so-called *rating-shopping*. *Rating-shopping* occurs when firms shop among different agencies for the highest rating and hold back lower conclusions.

Byoun and Shin (2002) used 221 unsolicited new ratings and 85 unsolicited rating changes as well as 27 solicited new ratings and 81 solicited rating changes in non-U.S. corporations (i.e., in 16 countries) between 1996 and 2002. The main objective of this research is to examine the effect of solicited and unsolicited ratings on stock prices. The authors concluded that low-grade and downgraded unsolicited ratings are much more profound to market's reactions than high-grade and upgraded ones. The empirical results also revealed significant negative market reactions associated with new low grades and downgrade announcements of unsolicited ratings. On the other hand, for solicited ratings, the research concluded that negative market reactions only accompany downgraded ratings. This indicates that solicited ratings are used by good firms to signal good performance indices to the market, unlike poor performance firms that choose not to signal. Consequently, unsolicited ratings signal negative information about a firm's performance in the market.

It is worth mentioning that many studies (Poon, 2003; Poon and Firth, 2004)[9] have discussed the major differences in treatments between solicited and unsolicited corporate/ bank ratings. The two studies used a standard sample selection model that accounted for self-selection into solicited status. The results demonstrate that unsolicited ratings tend to be lower than solicited ones after controlling for differences in key financial characteristics, sovereign risk and sample selection. In addition, firms that ask for ratings have stronger financial profiles in terms of liquidity, profitability, leverage and financial flexibility than issuers that do not ask for ratings. Moreover, firms operating in countries with an investment-grade sovereign rating have higher ratings than in countries with a speculative-grade sovereign rating. This means that sovereign ratings positively affect ratings.

[9] Poon (2003a) using pooled time-series cross-sectional data on 265 insurance companies in 15 developing countries rated by S&P during 1998-2000. The dependent variable was LTR issued by S&P. The independent variables were five dummy variables that refer to the solicited rating, Japanese issuers and sovereign ratings (three levels). This is in addition to four financial variables (EBIT interest coverage and return on assets as proxies for firm profitability, total debt to capital as a proxy for firm capital structure and short-term debt to total debt as a proxy for firm financial flexibility). Ordered-probit model was used. The author concluded that rating agencies have differently weighted the same financial indicators in issuing ratings to Japanese and non-Japanese issuers. In addition, the results indicated that capital structure and financial flexibility (profitability) are negatively (positively) statistically significant for LTRs. Profitability and sovereign credit risk were the two major factors used to determine the LTRs. In the same context, Poon and Firth (2004) considered Fitch's ratings of 951 banks in 82 countries.

Along with this, Butler and Cornaggia (2012)[10] examined the role of agency-firm relationships in the rating process. They used cross-sectional regression to examine whether or not a favourable rating assigned to issuers is the result of their paying high rating fees. The authors concluded that there is no obvious conflict of interest between RAs and issuers. That is, solicitation of a rating encourages RAs to rely more on so-called *soft* information and place less weight on *hard* information.[11]

Similarly, Gan (2004)[12] examined whether or not RAs (in particular, S&P and Moody's) use consistent standards in solicited and unsolicited ratings. The author addressed this question by looking initially at the *ex ante* analysis, which states whether unsolicited issues are indeed given lower ratings than solicited issues, with the same observable issuer characteristics. This was followed by looking at the *ex post* analysis, which states whether unsolicited ratings perform better than solicited ones after the issuance of the rating while controlling for issuers' characteristics.

The author pointed out that both RAs issue significantly lower ratings to unsolicited issues. The main message of this study was that the performance of solicited and unsolicited issues is significantly the same. Perhaps, on the one hand, this is inconsistent with the so-called *punishment hypothesis*, in which RAs rate unsolicited issuers lower than they deserve so as to force future payments. On the other hand, this approach seems consistent with the private-information hypothesis, in which RAs issue lower ratings for unsolicited issues because of self-selection based on private information. Consequently, the author concluded that, holding

[10] Butler and Cornaggia (2012) used a sample of 360 issued bonds by 153 firms during 1997 for which the firm hired at least one RA. The paper used high fees paid to RAs by issuers as a proxy for solicited rating and those with medium or low rating fees as a proxy for unsolicited rating. Authors used 'hard' information terminology for public information and 'soft' information terminology for private information that come directly from issuer.

[11] Authors have excluded bonds with zero rating fees from their sample, which may have created a selection problem in their sample.

[12] The author used a sample of 1,410 bond issues by 303 firm rated by both S&P and Moody's during 1994 to 1998. In line with Bulter and Cornaggia (2012), the author used rating fees reported in the registration statement to distinguish between solicited and unsolicited issues.

public information constant, firms with more favourable private information self-select into the soliciting group.

In addition, Van-Roy (2006) examined the possibility of whether or not Fitch treats solicited and unsolicited bank ratings differently. The self-selection hypothesis and public-disclosure hypothesis are the two main hypotheses examined in this study. The former hypothesis states that better banks may self-select to be rated and that poor quality banks may not request to be rated. The latter hypothesis states that the significance of private information to rating agencies is minimised if banks with unsolicited ratings reveal extensive public information that compensate for the absence of private information.

The empirical results of Van-Roy (2006) reveal that the ratios of loan loss provision to net interest revenue and the ratio of net loans to total assets (disclosure index and return on assets) have a significantly negative (positive) impact on individual bank ratings. Interestingly, the author found that financial and nonfinancial characteristics are not the main reason for the difference in treatment between solicited and unsolicited ratings. However, unsolicited ratings tend to be lower as they are based mainly on public information. Thus, the results reject the self-selection hypothesis and are consistent with those of the public-disclosure hypothesis. This means that banks that publish extensive public information do not receive lower unsolicited ratings. However, the relevance of these results to other regions is questionable as the research data are extracted from banks located in Asia only.

In the same context, Poon et al. (2009) used time-series cross sectional data from 460 commercial banks in 72 countries, excluding United States, that had solicited and unsolicited long-term credit ratings in local currency issued by S & P from 1998 to 2003. Controlling for the effects of diverse financial profiles and self-selection bias, the main objective of the study was to identify and examine how and why solicited and unsolicited ratings may differ.

In line with Van-Roy (2006), the results of Poon et al. (2009) showed that unsolicited bank ratings are lower than solicited ones. This result can be understood in the light of differences in financial profiles and solicitation status across solicited and unsolicited bank ratings. Following this, it has been proposed that among other factors, country sovereign risk, bank profitability and bank size impose crucial influences on bank ratings. The empirical results revealed that return on assets (the ratio of loan loss reserve to gross loan) is positively (negatively) significant for Standard & Poor's long-term rating. Thus, large and profitable banks with relatively low non-performing loans to gross loans located in countries with high sovereign ratings tend to have higher Standard & Poor's long-term ratings than small and less profitable banks located in countries with low sovereign ratings. Poon et al. concluded that the solicitations do matter to bank ratings and that the impact of solicitation on bank rating is much more significant than that caused by differences in financial profile.

2.3 The methodology of bank rating

There is a strong relationship between sound and stable financial systems and the goal of sustainable macroeconomic and structural policies in the Middle East region. The sound financial systems result in wise allocation of resources and thus are considered a prerequisite for economic stability. On the other hand, macroeconomic volatility results in a negative impact on financial stability. In the Middle East region, financial stability and soundness are strongly affected by the soundness of the banking system, mainly because of the absence of capital markets' role in resource allocation. This role highlights the significant importance of bank FSR as an indicator of the soundness and stability of the banking system (Laruccia and Revoltella, 2000).

Banks are special and their unique and opaque characteristics, functions, operations, regulations, asset-structure, involved risk, and state protection laws necessitate special rating methodologies. Morgan (2002) noted that the two major bond RAs (i.e., Moody's and S&P) have more split ratings for banks than for corporations, which suggests that bank opacity hinders RAs' ability to quantify banks' risks and thus to issue a correct rating is difficult.[13] This risk stems from the nature of bank assets, especially loans and trading assets, for which uncertainty is hard to observe, as well as banks' high leverage, through which agency problems may be introduced.

In general, bank rating methodology can be framed by RAs into a set of questions to assess bank's stability. RAs want to know more details about banks' loan portfolios, in terms of economic sector, country risk, and currency; the breakdown between secured and unsecured lending; the rules and regulation imposed by the bank on loans to individual borrowers and the procedures for setting such rules and regulations; how banks assess and define doubtful and/or non-performing credits; disclosure of off-balance-sheet items and the amount of loan loss provision allocated by the bank. RAs are interested in knowing a breakdown of trading and investment securities portfolios as well as portfolios managed by the bank in terms of type of instruments (equity or fixed interest), the issuer, currency and maturity.

It is also should be noted that RAs review bank interest rates and currency sensitivity. In addition, rating analysts check whether or not the inner or hidden reserves can be officially recognised and qualify as adequate capital. This is followed by calculating the bank's capital weighted risk ratio as per the Basel G10 agreement. It is noteworthy that RAs must pay close attention to the makeup of the capital and examine both tier 1 and tier 2 capital. Moreover, RAs focus on the nature and characteristics of the bank's revenue stream and expenses. In addition, information about the ownership structure, contingent liability against the bank and

[13] Split ratings indicate that banks or firms receive different ratings from two or more RAs. The main objective of Morgan (2002) was to identify the main differences between the two RAs (Moody's and S&P) in determining bank rating assignments using ordered logit regression.

reports on the bank by the national supervisory authority's and independent auditors are information needed by RAs to assess the creditworthiness of banks.

2.3.1 CAMEL approach

CAMEL (i.e., capital adequacy, asset quality, management, earnings and liquidity) is an analytical approach suggested by Moody's to assess a bank's overall safety, stability and soundness.[14] As mentioned earlier, individual bank ratings are published by Moody's, Fitch and CI, which issue BFSRs, FBRs and FSRs respectively. However, S&P has no publicly available equivalent to these individual bank ratings.

2.3.1.1 Capital adequacy

Bank equity capital, the first element, provides a buffer against unexpected losses and thus assists banks to survive, thereby overcoming the risk of insolvency. That is, a bank's equity capital acts as the last resort or defence against failure because any losses suffered by a bank are potentially written off against capital. In the case of unavoidable bankruptcy, Bras and Andrews (2003) stated that bank equity capital protects depositors, creditors and investors against expected losses that should be borne by them. It is worth mentioning that the size of a bank's equity capital and its capital adequacy (i.e., the proportion of the bank's capital relative to its risk) are considered by RAs to be the most important factors in the analysis of bank creditworthiness. Rawcliffe and Andrews (2003) pointed out that bigger banks (in terms of absolute size of equity) are more likely to be significant to their domestic economies as the probability of receiving external support exists strongly, if needed, and thus decreases the risk that the bank will default. Many studies in the literature have stated that high capital strength ratios result in better bank ratings (Laruccia and Revoltella, 2000; Pasiouras et al., 2006,

[14] In 1997, a sixth component, a bank's sensitivity to market risk was added to the CAMEL model; hence, the acronym was changed to CAMELS. The main objective of this measure is to test the impact of changing market conditions on bank profitability and the value of its assets and liabilities.

2007; Poon et al., 2009; Poon and Firth, 2005; Van-Roy, 2006).This implies that well-capitalised banks tend to acquire higher bank FSRs.

2.3.1.2 Asset quality

Asset quality (e.g., diversification, loan growth, adjusted returns, credit policy and provisions)[15] is the second crucial element of CAMEL. Asset quality refers basically to the quality of the bank's earning assets, which is composed mainly of the bank's loan portfolio (credit risk) and securities portfolio (market risks) as well as off-balance-sheet items (e.g., guarantees, letters of credit and derivative instruments). The importance of bank asset quality examination to RAs stems from the fact that a bank with poor asset quality is associated negatively with its profitability by reducing the spread between interest income and provision costs; thus a bank's net profits erodes over time.

Accordingly, a bank with poor asset quality is closer to insolvency and thus will be associated with low FSRs. Poon et al. (1999) found that the most important factors used to classify Moody's bank ratings are loan provision information and bank risk, respectively. Laruccia and Revoltella (2000), Poon and Firth (2005), Pasiouras et al. (2006), Van-Roy (2006), Poon et al. (2009) and Laere et al. (2012) found that banks with better asset quality (in terms of loan portfolio) have better probability of acquiring a high bank rating.

2.3.1.3 Earnings

Along with the above two elements, profitability (return on equity [ROE] and return on assets [ROA], stability of income streams, trend and track of profits, dividends payout potential) is the third element used in the assessment of banks current financial performance and growth prospects. Profitability is an important area for RAs to analyse as bank income ultimately

[15] In spite of the increasing sophistication of banks and growing market risk, the principal risk for most banks remains credit risk, which is reflected in the analysis of asset quality (e.g., loan portfolio including type, size, maturity, currency, geographical distribution and economic sector).

affects its survival and existence. Profitability is a quantitative measure of management's ability to utilise assets efficiently to create value for shareholders and maintain and improve capital soundness. In the same context, in the analysis of profitability, it is important to determine the extent of diversification (types and sources) of earning streams. Poon et al. (1999), Laruccia and Revoltella (2000), Poon and Firth (2005), Pasiouras et al. (2006), Van-Roy (2006), Pasiouras et al. (2007) , Poon et al. (2009) and Laere et al. (2012) concluded that profitable banks tend to obtain high bank ratings, and insolvent banks seem to have problems generating adequate profits (Wheelock and Wilson, 2000).

2.3.1.4 Management quality

The fourth element is management quality (e.g., experience, reputation and technical skills, honesty and integrity, eagerness to keep well regulated environment, strategic planning and the ability to keep effective internal and external communication), which is a subjective element in bank analysis. Management quality is the ability of managers to generate the maximum revenue from available earning assets and to control bank costs. Therefore, management efficiency in generating revenues and managing expenses is another factor that assists RAs to understand the creditworthiness of a bank and thus to assign the appropriate bank rating (Pasiouras et al., 2006).

2.3.1.5 Liquidity

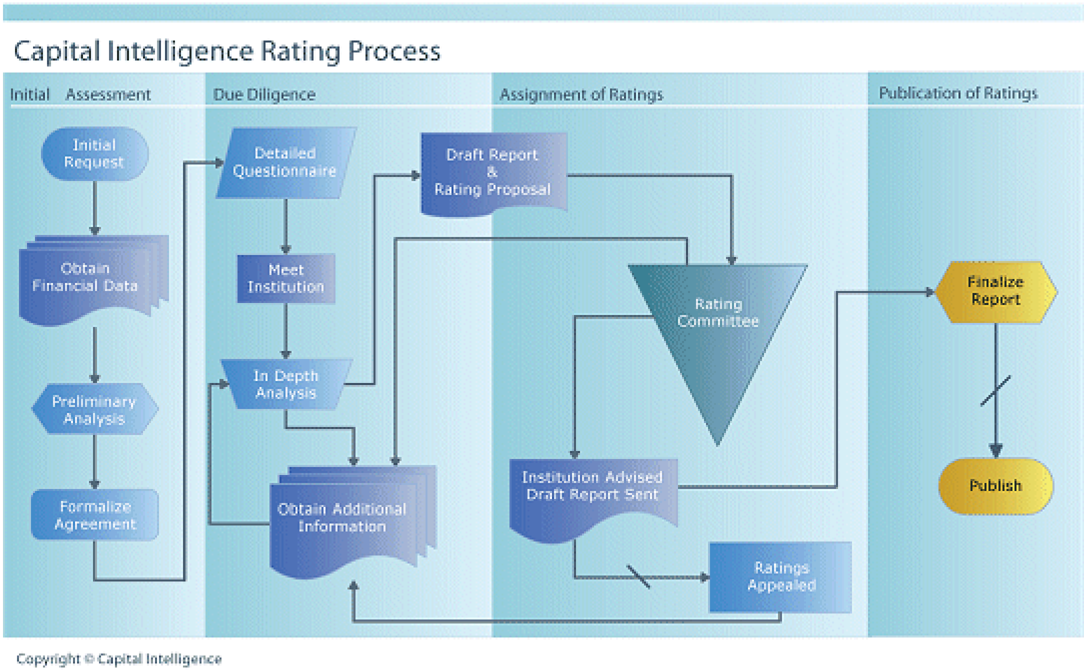
The fifth component is liquidity (stability of customer base, whether loans and funding are well matched and overall liquidity position), which is an important evaluation element for both good banks and stressed ones. Banks are highly concerned with liquidity risk; that is, the chance that bank will not be able to meet its current financial obligations (e.g., those of depositors) because of insufficient current assets such as cash and quickly marketable securities, especially during economic recession (Golin, 2001). Laruccia and Revoltella

(2000) found that banks with low net loans to assets ratio (good liquidity position) tend to obtain better BFSRs assigned by Moody's. Poon and Firth (2005) and Pasiouras et al. (2006) concluded that banks with high loans to total asset ratio (poor liquidity position) acquire low FBRs.

2.3.2 Capital Intelligence bank rating methodology

The CI rating process is summarised in Figure 2-1. CI adopted a more specialised approach to the assessment of bank stability (Capital Intelligence, 2012). This approach considers operating environment, ownership and governance, franchise value, management and strategies, risk profile and financial profile as major determinants of bank's stability.

Figure2.1: CI's rating process



Source: Capital Intelligence (2012)

A bank's operating environment includes the evaluation of the country's economic structure; political stability; country's legal system; the developments in the money, capital and real estate markets; and government policies changes that might impact the banking industry. CI examines the role of the stability of the bank's ownership structure and the eagerness of owners to support the bank in hard times. In line with this, the bank's position in the domestic banking sector also is examined by CI in terms of market share of assets and various business sectors. This is considered as an essential indicator of bank earnings performance, both current and future.

This is followed by CI's judgement about the organisational structure of the bank, management's degree of independence from the bank's owners and the management qualification needed to plan and react to changes in the environment. CI evaluates bank's risk profile, which comprises market, operational and legal risks. Market risk is related directly to unpredicted fluctuations in market prices (interest rates, exchange rates, equity prices and prices of final goods) and is closely associated with asset and liability management. Operational risk may arise as a result of inadequate or failed internal and/or external processes and systems. In line with these concerns, various sources of conflict between market participants may lead to legal risk.

CI concludes its process by assessing the bank's financial profile, which includes asset quality, capital, liquidity and profitability. Finally, CI assesses these factors and issues bank FSRs according to a score based on these assessments. In this thesis, one objective is to assess the contribution of bank's financial and nonfinancial profile in the assignment of high- and near-high FSRs to formulate financial strategies for bank managers who seek high FSRs. Another aim is to identify the relative importance of financial and nonfinancial variables for CI analysts in the assignment of high FSRs and thus assist bank mangers in designing the relevant financial policies that promote banks' high FSRs.

2.4 Bank rating and bank capital structure

In the process of financial intermediation, banks face severe competition, which forces them to incur various types of financial and nonfinancial risks. It is known that the growth of any business is linked with greater risk, as higher risk must be compensated with higher return. This ultimately forces entities to trade-off between risk and return. Risk arises from expected and unexpected events. In the case of expected losses, banks can overcome risk by appropriate pricing methods. The unexpected loss is created mainly by the bank itself and it must be covered by the mandatory capital.

Accordingly, the importance of bank CS and the need for an adequate capital is recognised. Because the capital allocation process is based on risk sensitivity, bank regulators seek to prevent or reduce the probability of bank failure. The goal is to enhance banks' stability, safety, soundness and prevent system disaster that eventually provide safeguard to bank depositors. It seems that ideal bank CS is of great concern for any bank because of the new international standards (i.e., Basel II), the severe competition between banks because of technological improvements and to boost bank financial strength to meet eventualities that may pose adverse financial impact. In this context, efficient bank ratings protect financial firms against unexpected losses and failure. It is obvious that efficient bank ratings are crucial in environments characterised by asymmetric information such as the Middle East region. Mishkin (2012) states that asymmetric information occurs when one party (principal) has inadequate information about the other party (agent) involved in a transaction that eventually may lead to inaccurate decisions. In the banking industry, the lack of, and in many other cases, the incomplete information about borrowers' creditworthiness provides an example of the existence of information asymmetry in the Middle East (Best and Zhang, 1993).

The literature shows that asymmetric information result in various kinds of moral hazard and adverse selection problems. It is noteworthy that adverse selection problem arises before entering into a financial transaction, while moral hazard problem does exist after the financial transaction has occurred (McCaskie, 1999). As far as the banking industry is concerned, these two problems may result in a failure in banks' credit system, a loss of depositors' confidence in the financial reserves systems and consequently a negative influence on bank FSR. On the macroeconomic perspective, these two problems may end up with a systemic banking crises causing a collapse in the financial system and thereby creating an economic crises such as 1997 Asian financial crises and 2008 global financial crises (Akerlof, 1970; Bester, 1985; Berndt and Gupta, 2009; Freimer and Gordon, 1965; Harris, 1974; Milgrom and Roberts, 1992; Stein, 1998; Stiglitz and Weiss, 1981).

The moral hazard problem is exemplified in the Middle East banks as far as they do not consider the full consequences and responsibility of their actions, and therefore have a tendency to act more risky than they would have otherwise. This source of risk is mainly due to the fact that the majority of Middle Eastern banks are government-owned. Therefore, banks' operations and decisions are protected intensely by the government. In addition, adverse selection problem occurs due to the fact that banks in the Middle East region may issue loans to customers without remunerate the associated credit risk appropriately. That is, customers' creditworthiness is not fully operationalized due to the banks' lack of complete information about customers.   To overcome this issue, the operation of banks in unsecured markets urges banks to maintain a sufficiently high FSR.

In the banking industry, *economic capital*[16] is defined as the amount of equity needed by a bank to cover, with a chosen confidence level, unexpected losses in its portfolio over a given time. Such a confidence level explains the bank's solvency standard (defined as one minus the probability of default for a representative bank). This implies that economic capital can be effectively linked to a rating category that historically displays the same solvency standard. Jackson et al. (2002) confirmed that a bank with an A rating is characterised by a 99.96%

[16] *Economic capital* is defined as the risk capital used by the bank to cover the three basic risks (market, credit and operational). In other words, economic capital is the amount of money needed for survival in the worst case scenario. Economic capital differs from regulatory capital in that the latter is the obligatory capital required by regulators to be maintained, whereas economic capital is the best estimate of the required capital that banks use internally to manage their own risk.

solvency standard; equally, a bank that seeks an A rating must reserve economic capital using the 99.96% confidence level. Jokivuolle and Peura (2006) pointed out that banks that seek the minimum rating target hold a capital buffer in excess of the minimum amount of economic capital.

Gordy and Howells (2006) emphasised that a bank that aims to have an adequate capital for an AA rating today might also want to have a 95% probability of remaining investment grade at the horizon. This constraint creates a buffer for economic capital. Jokivuolle and Peura (2006) also assumed that external RAs determine bank ratings based on a comparison between the bank's actual capital and its economic capital. That is, the bank's actual capital must exceed its economic capital within a confidence level implied by the minimum rating target (such as 99.96% over a one-year period for an A rating) to achieve the minimum rating target. Accordingly, an increase in confidence level will result in an increase in economic capital. This implies that to achieve a better bank rating requires an increase in the bank's capital.

2.4.1 Principal-agent relationship

Before proceeding further, it seems helpful to shed light on what is known in the literature as the *principal-agent relationship*. In this regard, the principal is the regulator and agents are the financial institutions. The regulator is supposed to monitor domestic financial institutions to safeguard the interests of depositors, among others. Capital adequacy as a buffer against losses and failure is among the main tools with which to monitor a bank's solvency position and bankruptcy avoidance (Murinde and Yaseen, 2004).[17]

[17] It should be noted that the stage of business cycle and the bank's financial situation determine how banks will respond to capital ratio pressures. During booms, banks issue new equity capital, and they cut bank loans during downturns. The reduction in lending, when banks are capital constrained, directly affects the real economy. This is mainly because the reduction in bank lending may not be fully offset by increases in lending from other financial intermediaries or markets. The credit crunch is the output that results from substitution of high-risk

Specific characteristics of banks explain why the theory of optimal CS for banks is somewhat different from that of nonfinancial firms. Simply, governments interfere in bank capital structure in two ways: (1) the government may provide under-priced guarantees (e.g., explicit deposit insurance and implicit guarantees of deposits and other liabilities), and (2) regulators play a crucial role in increasing costs associated with capital levels considered insufficient by the regulators. In this context, the role of bank deposits in affecting bank financial decisions , especially CS, should be considered in line with the ability of banks to minimise the cost of financial intermediation and the effects of moral hazard and adverse selection (Osterberg, 1990).

In line with this, high leverage and illiquid assets financed by short-term liabilities are among the major characteristics of banking-industry-specific risk. This may explain why financial institutions have much higher leverage than nonfinancial corporations. Along with this, highlighting the differences between developed and less developed financial systems is perceived as a radical issue. In less developed systems, policymakers must carefully consider consequences of information asymmetry and banking regulations (Vives, 2006).Obviously, the consequences of financial failure are vital in terms of serious social costs, the contamination of other financial institutions, and ultimately, the economic system as a whole. This puts pressure on every country to develop and implement strict policies to assure the safety and soundness of its banks.

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assets, such as commercial loans, into less risky assets, such as government securities, that will end up with a significant decline in the credit supply to borrowers. Consequently, reduction of bank loans will lead to a substantial decline in the investment demand and a real growth slowdown. This apparently delays firms' investment plans and may lead to reduction in numbers of workers to cut costs. It is essential to explain that the cause of bank capital constraints may be a substantial increase in provisions and write-offs, a general decline in bank loan demands, and/or banks' concern about deterioration of their credit quality. In addition, banks with less capital will be more aggressive in pricing loans, forcing other banks either to reduce loan prices or to lose market share.

The main theme of the standards of BIS, which was established in 1974 by the G10 countries and Switzerland, is that investment in high-risk assets forces banks to increase their capital. BIS aimed mainly to improve soundness and stability of the international banking system in response to the gradual increase of risk after the globalisation and deregulation of financial systems in a large number of countries, especially the developing countries. Many studies have shown that stiffer capital regulation—risk-based CS—is a necessary component of explanations of the decline in loan growth, which eventually results in a credit crunch (Berger and Udell, 1994; Brinkmann and Horvitz, 1995; Furfine 2000; Furlong, 1992; Haubrich and Wachtel, 1993; Jacques and Nigro, 1997; Lown and Peristiani, 1996; Naceur and Kandil, 2007; Rime, 2001; Wagster, 1999; Wall and Peterson, 1987). The following section focuses on banking regulations. A number of important questions can be raised in this regard. Whether or not regulation of the banking industry promotes competitiveness, efficiency and stability of the financial system is among these questions.

2.4.2 Basel I and II

In 1988, the Basel Committee on Banking Supervision (BCBS) started to set up rules and regulations intended to enrich the stability and soundness of the international banking system. This concluded with the development of a new framework, which known as Basel I.[18] Basel I requires banks to have a Tier 1 ratio of at least 4% and a total capital ratio of at least 8% (with Tier 2 not exceeding 50%). Because it can be expensive to issue new capital, this scheme leads to a preference for less risky assets (Naceur and Kandil, 2007).In general, risky assets (e.g., commercial loans and consumer instalment loans) require the maintenance of total

[18] A bank's capital was defined as comprising two tiers: Tier 1 (or *core*) capital includes the book value of common stock, non-cumulative preferred stock, share premiums, retained profit, general and legal reserves; and Tier 2, (or *supplementary*) capital includes revaluation of assets, undisclosed reserves, general provision and reserves, hybrid instruments (i.e., cumulative preferred stock), long-term subordinate debt and investment fluctuation.

equity capital equal at 8% of the asset's book value. On the other hand, riskless assets (e.g., cash and government debt) incur no capital requirements.[19]

Critiques of Basel I were raised against the equal risk-weighting given to all credit regardless the high or low quality of the credit; which consequently led to incoherence between banks' capital levels and their credit quality. In addition, Basel I ignored the maturity structure of credit exposure for capital charges[20] and failed to take advantage of the availability of certain credit risk-mitigation techniques such as cash margins, collateral security, and so on. Also, Basel I did not recognise the portfolio diversification effect on credit risk; however, this was captured later by market risk. Finally, Basel I did not impose capital charges for operational risk, which is considered as an important source of risk and may be, at times, more overwhelming than credit risk.

On the contrary, it is worth mentioning that the introduction of Basel I for bank capital reignited interest in the effects of bank capital regulations (Dahl and Shrieves, 1990; Weber and Darbellay, 2008).The main conclusions of later studies were that regulatory minimum capital constraints are crucial to influence financing decisions made by a significant subset of banks. A positive relationship between bank capital and bank risk-taking has been confirmed by vast number of studies (e.g., Aggarwal and Jacques, 1998; Edtiz et al., 1998; Jacques and Nigro, 1997; Shrieves and Dahl, 1992).According to this regulatory hypothesis, banks are encouraged by regulators to increase their capital in accordance with the amount of risk taken.

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[19] The risk baskets are divided into four parts: (1) 0% for cash, claims on central governments denominated and funded in national currency (sovereigns), claims on all Organization for Economic Co-operation and Development (OECD) central governments and claims on central banks. (2)20% for claims on multilateral development banks and claims guaranteed by these banks, claims on banks incorporated in OECD and loans guaranteed by these banks, and claims on banks outside of OECD with maturity of up to one year. (3)50% for loans secured by mortgages on residential property. (4)100% for claims on corporate, claims on banks outside of OECD with maturity of more than one year, claims on central governments outside of the OECD and not denominated and funded in national currency, and all other assets.

[20] The accord ignores the fact that there is greater risk of default accompanied by long-term exposure than the short-term exposure.

On the contrary, an opposite hypothesis suggests a negative relationship between capital and risk. This is known as the *moral hazard hypothesis*, which stems from the unintended consequences of regulatory actions. As discussed by Kahane (1977), Koehn and Santomero (1980) and Kim and Santomero (1988), banks could respond to regulatory pressures to increase their capital by increasing asset risk. The Basel Accord was updated in the early 1990s, by adding a new element: market risk resulting from changing market conditions (e.g., share prices and interest rates). The proposed amendment required that the ratio of capital to credit risk and market risk should be greater than or equal to 8%.

As a consequence of the aforementioned criticism of Basel I, the BCBS proposed a more risk-sensitive approach in Basel II, which is based on three pillars of banking safety and soundness: minimum capital requirements, prudential supervision process, and market discipline.[21] The new accord introduced two main approaches by which to calculate bank capital requirements. The first alternative, called the *standardised approach*, typifies a portfolio of bank loans by risk categories; that is, the risk weight assigned to each category is based on the counterparty risk assessment performed by international RAs. This approach has magnified the role of RAs in the development of bank CSs on a global scale. Apparently, RAs came to serve as regulatory tools in financial market prudential oversight.[22] The second alternative, called the *internal ratings-based* (IRB) approach, depends entirely on banks' internal rating systems for credit risk evaluation in which bank supervisors are the key players (Weber and Darbellay, 2008).

[21] For the prudential supervision process, banks' internal assessment procedures are the full responsibility of national supervisors with additional authority and right to impose additional capital requirements. For the market discipline and disclosure portions of Basel II aim to increase transparency by using enhanced disclosure requirements for banks. Such transparency will improve the ability of market participants to evaluate effectively the bank's risk profile.

[22] Basel II has categories (0%, 20%, 50%, 100% and 150% for short-term government bonds, exposure to OECD banks, residential mortgages, unsecured commercial loans and borrowers with poor credit rating, respectively) depending on the credit rating of the borrower. Although a 100% risk weight means a full capital charge equal to 8% of the value, a 50% risk-weight requires a capital charge of 4% of that value.

In spite of the fact that the second approach is more expensive, advanced and yields a much higher regulatory capital level, it is obvious that both approaches are costly and complex.[23] Basel II added a new type of risk: operational risk, defined by Basel Committee on Banking Supervision (2001) as 'the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events'[24] (p. 2). Three methods are used to calculate operational risk capital charges: (1) the basic indicator approach in which banks must hold capital from operational risk equal to fixed percentage of gross income, (2) the standardised approach[25] and (3) the internal measurement approach.[26]

Accordingly, the basic capital requirements for banks (≥ 8%) can be expressed as the ratio of bank capital to credit, market and operation risks. Hence, supervisors in some emerging markets have applied much higher minimum capital levels than Basel's 8%. For example, the minimum capital requirement in Argentina is 11.5% plus 1% for market risk exposure, and in Singapore, the minimum is 12% (Jackson et al., 2002). Raghavan (2004) also noted that Basel II was rejected by China, where the minimum capital requirement is determined mainly by the China Banking Regulatory Commission. In the early 2000s, regulators discussed the inclusion of other types of risk, such as liquidity risk, warehousing risk, reputational risk and concentration risk. In contrast to Basel I, Basel II has succeeded in precluding banks from taking excessive risk. This is justified as more capital requirement will be needed to hold

[23] The two approaches are computed by multiplying the following three parameters: estimates of the probability of default, loss given default and exposure at default. The difference between the two approaches is that banks that apply the advance approach will compute the three parameters internally and independently, which is not the case under the foundation approach.
[24] This definition includes legal risk
[25] Bank activities are divided into standardised business unit and business line. For each business line, an indicator measures the size and volume of bank activity in that area. The capital charge for operational risk is calculated by summing the product of the indicator for each business line to its capital factor, which is mainly set by supervisors.
[26] For this approach, the overall capital charge is simply the product of gamma and expected loss. Expected loss is the product of exposure indicator, probability of loss event and the loss given that event. Gamma is a factor supplied by supervisors that for each business line/risk type combination.

risky positions. Consequently, banks will be more cautious about going into riskier businesses. Eventually, financial stability will be reached.

On the other hand,Weber and Darbellay (2008) criticised Basel II, especially the standardised approach, out of concern that banks will concentrate more on obtaining high credit rating than on the quality of underlying assets. The authors added that conventional banking activities performed by banks to monitor their customer will diminish. This is mainly because banks are over-reliant on RAs to collect and gather information about borrowers, thereby enhancing financial instability, which was initially observed in the subprime crisis. In addition, measurement of bank capital requirements using credit rating also was criticised because of the ratings' procyclical effects.[27]

A study by the BCBS on the impact of Basel II on 365 banks in 43 countries showed that capital requirement and risk in banks with more retail activities were low (Basel Committee on Banking Supervision, 2003). This may encourage banks located in large G10 countries to increase investments in retail activities. In line with this finding, it seems that the introduction of Basel II hindered asset securitisation in large banks because of the substantial rise in capital requirements accompanied by the inclusion of more securitised assets in bank portfolios.[28] Moreover, evidently, the degree of specialisation within the banking industry is positively and significantly related to the level of capital requirements. The introduction of IRB approaches creates more pressures on banks, especially the large ones. This is not the

[27] This was supported by the notion that RAs tend to upgrade borrowers' credit ratings during economic booms and vice versa during financial crises. Such trends negatively impact banks' financing during recession and decrease capital reserves during economic booms.

[28] Traditionally, banks kept the originated loans on their balance sheets and monitored them for their entire durations; the securitisation process allows banks the possibility to offload credit risk from their balance sheets and transfer them to other investors.

case for small banks that will be forced to implement that less costly standardised approach, thus segmenting the banking industry into two tiers.[29]

2.4.3 Bank CS and financial variables

The endogenous relationships between banks' CS and financial variables stem from the fact that all changes in bank income statements affect the equity position according to the balances of the accounting equation. Table 2.1 summarises the endogenous relationship between banks' CS and financial variables.

Table 2.1: Endogenous relationship between bank CS and financial variables

Financial Category	CS Endogenous Relationship	Relevant Literature
Asset quality	The ratio loan loss provision to net interest revenue (LLPNIR) negatively affects bank CS because high loan loss provisions increase total operating expenses. This results in a decline in bank net income and thus bank net worth or equity capital (i.e., bank assets/liabilities) will decrease in value. The ratio of loan loss reserve to impaired loans (LLRIL) negatively affects bank CS because high loan loss reserves result in a decrease in the value of the bank loan portfolio and thus a decrease in the value of bank assets. This results in a decrease in bank net worth. The ratios of impaired loan to gross loans (ILGL), impaired loans to equity (ILE) and unreserved impaired loans to equity (UILE) negatively affect bank CS because high levels of impaired loans result in a decline in the value of bank assets. Accordingly, bank equity capital is negatively affected. The ratio of net charge-off to net income before loan loss provision (NCONIBLLP) negatively affects bank CS because high net charge-off leads to a decrease in bank net income and thus low equity capital.	Ahmed et al., 1999; Angklomkliew et al., 2009; Balla and McKenna, 2009; Bouvatier and Lepetit, 2008; Craigwell and Elliott, 2011; Fecht and Wagner, 2009; Floro, 2010; Ghosh, 2007; Laeven and Majnoni, 2003
Capital Adequacy	Tier 1 ratio (TR) and total capital ratio (TCR) positively affect bank CS because both ratios contain the main elements of bank CS ratio. The ratios of equity/net loans (ENL), equity/liabilities (EL) and equity/deposit and	Altman and Sounders, 2001; Ayuso et al., 2004; Cantor, 2001; Diamond and Rajan, 2000; Dince and Fortson, 1972; Fama, 1980; Gambacorta and Mistrulli, 2004; Gardener, 1981, 1990;

[29] It is worth noting that to overcome deficiencies in financial regulations revealed by the global financial crisis, the BCBS introduced on 16 Dec. 2010 a new global regulatory standard—Basel III—for bank capital adequacy and liquidity. Basel III strengthens bank capital requirements and introduces new regulatory requirements for bank liquidity and leverage. However, some estimates indicate that implementation of Basel III will decrease annual GDP by 5% to 15%.

	short-term funding (EDSTF) positively affect bank CS because the main component of these ratios is bank equity capital. The ratios of capital funds to assets (CFTA), capital funds/net loans (CFNL), capital funds/deposit and short-term funding (CFDSTF) and capital funds/liabilities (CFL) positively affect bank CS. This is mainly because bank capital funds comprise bank equity capital, hybrid capital and subordinated debt. The ratio of subordinated debt/capital funds (SDCF) negatively affects bank CS because the percentage of subordinate debt in capital funds increases and bank equity capital decreases. Equity multiplier (EM) negatively affects CS as equity multiplier ratio is the inverse of bank CS ratio.	Kahane, 1977; Lackman, 1986; Pringle, 1974; Santomero and Watson, 1977; Sealey, 1983; Sharpe, 1978; Shehzad et al., 2010; Talmor, 1980.
Credit Risk	The ratio of Net Charge Off/Average Gross Loans (NCOAGL) negatively affects bank CS. This is mainly because high net charge-off leads to a decrease in bank net income and thus inversely affects its equity capital. The ratios of Loan Loss Provisions/Total Loans (LLPTL) and Loan Loss Provisions/Equity (LLPE) negatively affect bank CS as high loan loss provision means an increase in bank total expenses. This decreases bank net income which ultimately decreases its net worth (i.e., equity capital) The ratios of Loan Loss Reserve/Gross Loans (LLRGL) and Loan Loss Reserve/Total Equity (LLRE) negatively affect bank CS. This is mainly because high loan loss reserve reduces the value of bank assets and thus its net worth.	Anandarajan et al., 2007; Bikker and Metzemakers, 2004; Eng and Nabar, 2007; Fonseca and González, 2008; Graham and Humphrey, 1978; Greenidge and Grosvenor, 2010; Jiménez and Saurina, 2006; Sinkey and Greenawalt, 1991.
Liquidity	The interbank ratio (IBR) positively affects bank CS as whenever the bank is net placer (i.e., amounts due from other banks are greater than those due to other banks), which means that bank total assets exceed bank total liabilities and thus a higher net worth. The ratios of net loans/total assets (LR), net loans/deposit and short-term funding (NLDSTF) and net loans/total deposit and borrowing (NLTDB) positively affect bank CS. This is mainly because well-operated banks are able to sell more loans to increase profitability. This increases the amount of undivided profit, which leads to an increase in bank equity capital. The ratios of liquid assets/deposit and short-term funding (LADSTF) and liquid assets/total deposit and borrowing (LATDB) positively affect CS as banks with high volumes of liquid assets relative to their liabilities will have higher net worth and thus higher equity capital.	Casey and Lannoo, 2005;Diamond and Rajan, 2001a, 2001b; Hatakeda, 2000; Gatev and Strahan, 2006; Loutskina, 2011; Sawada, 2010; Wagner, 2007.
Profitability	The ratios of net interest margin (NIM), net interest income/average assets (NIIAA), other operating income/average assets (OIAA), recurring earning power (REP) and pretax	Albertazzi and Gambacorta, 2009; Angbazo, 1997; Claeys and Vennet, 2008; Demirguc-Kunt and Huizinga, 1999; DeYoung and Rice, 2004;

	operating income/average assets (PTOIAA) positively affect bank CS. This can be explained as banks with high profitability can retain some of their profits for future transactions. This results in an increase in undivided profit accounts and thus an increase in bank equity capital in general. The ratios of noninterest expense/average assets (NIEAA) and non-operating items and taxes/average assets (NOITAA) negatively affect bank CS as banks that pay higher interest and/or noninterest expenses negatively affect overall profitability. Accordingly, banks' ability to retain profits for future use is hindered. This results in lower undivided profits and thus lower bank equity capital. Return on average assets (ROAA) and return on average equity (ROAE) positively affect bank CS. An efficient bank is able to generate the maximum amount of earnings from available assets and equity. This leads to higher profitability and thus higher bank net worth. Dividend pay-out (DPO) negatively affects bank CS. This is mainly because higher payout ratios results in lower undivided profit accounts. This ultimately inversely affects bank equity capital. The ratios of income net of distribution/average equity (INODAE) and non-operating income/net income (NOINI) positively affect bank CS in the essence that an increase in income, whether from operating or non-operating revenues, will eventually lead to an increase in undivided profits and thus bank equity capital. Cost-to-income ratio (CIR) negatively affects bank CS. In general, banks face a problem in controlling overhead or the cost of bank activities. This results in a dramatic decline in profitability, which eventually leads to a decrease in undivided profits and thus bank equity capital. The ratios of net profit margin (NPM), tax management efficiency (TME), asset utilisation (AU) and expense control efficiency (ECE) positively affect bank CS. This is mainly because well-operating banks efficiently manage their expense-control programs. In addition, they implement proficient service-pricing policies and minimise their tax exposure. This leads to higher profitability and thus more undivided profits accumulate. This results in an increase in bank equity capital. Operating efficiency ratio (OER) negatively affects bank CS. It is notable that a high operating efficiency ratio indicates an expense-control problem or a decline in revenues. Thus, profitability and undivided profit accounts are negatively affected. This leads to a decrease in bank equity capital.	DeYoung and Roland, 2001; Dietrich and Wanzenried, 2011;Fonseca and González, 2008; García-Herrero et al., 2009; Ho and Saunders, 1981.

2.5 Bank ratings: Empirical findings

The relevant literature includes few studies on bank ratings and bank financial characteristics. A pioneering study on this subject was performed by Poon et al. (1999) using data from 1997 and a sample of 130 banks in different countries.[30] The main objective of the study was to predict Moody's BFSR[31] using bank-specific financial data and including an aggregate measure (between 0 and 100) of the bank's country's economic, political and financial risk (i.e., country effect). The authors also examined whether the information provided by BFSR is the same as that contained in traditional debt ratings. The method used was an ordered logistic regression model.

Their empirical results reveal that BFSR provides similar but not identical information to that contained in traditional debt ratings (both long- and short-debt ratings). Poon et al.'s (1999) results also show that the effect of country risk on BFSR is insignificant. This can be explained by the large similarity in banks' financial disclosures across countries and the maintenance of minimum capital adequacy ratios required by the BIS. In addition, the study found that loan provision, risk and profitability are the most important determinants of BFSR, respectively. Finally, Poon et al. concluded that the inclusion of short- and long-term debt ratings enhances the predictive power of the models.

Laruccia and Revoltella (2000) also predicted Moody's BFSR using data from a sample of 212 banks operating in developing and transitional economies (38 in East Europe, 106 in Asia

[30] The financial variables used in this study were from 1996.

[31] It is worth noting that the basic difference between Moody's BFSR and Moody's long-term deposit rating is that the latter concerns the bank's ability to repay foreign and/or domestic currency deposit obligations on time. That is, long-term bank deposits reflect the amount of country risk in which the bank is located. However, Moody's BFSR represents Moody's opinion of a bank's intrinsic safety and soundness and thus excludes certain external credit-risk and credit-support elements that are covered by Moody's long-term deposit rating. BFSR is an adequate measure of the probability that a bank will require external support from its owners, official institutions or from its business group. Accordingly, the BFSR provides an effective evaluation of the fundamental stability of each bank.

and 68 in South America). The main objective of their work was to identify the main determinants of overall banking system soundness and stability. Additionally, this paper focused on the construction of a microeconomic model to predict Moody's BFSRs using different econometric techniques (e.g., linear regression, logistic regression and a neural network).

The empirical results revealed that the neural network model explains 76.7% of the variance of the dependent variable, and the equivalent figure for the linear regression model explains 73.5%. The logistic model explains only 71%. Laruccia and Revoltella's (2000) results showed that the effect of country risk on BFSRs is highly significant in the models, which conflicts with the results reported by Poon et al. (1999). In addition, the findings conclude that all of the financial ratios had the expected sign for sensitivity. Banks with high BFSRs are associated with high equity-to-total asset ratios (i.e., well-capitalized banks), low cost –to-income ratios (i.e., highly profitable banks), low net loans-to-total assets ratios (i.e., highly liquid banks) and low loan loss reserve-to-gross loans ratios (i.e., better quality of loan portfolio).

Poon and Firth (2005) conducted a study based on FBR in 2002 for a sample of 1,060 banks in 82 countries. The main objective of this paper was to distinguish the differences between shadow (unsolicited) and non-shadow (solicited) FBRs and whether the financial characteristics of banks with shadow ratings differed from those with non-shadow ratings. The method employed was Heckman's two-step treatment estimation method. A piece of information derived from this study is that there is a significant difference in distribution between shadow and non-shadow FBRs. This difference stems from the fact that non-shadow FBRs are higher than shadow FBRs.

Poon and Firth (2005) suggested that this difference is based on many reasons: (1) banks with poor financial profiles will not seek ratings and thus will receive low shadow ratings; (2) the significant difference in levels of information used for shadow and non-shadow ratings matters; and (3) the nature of shadow rating, which is based entirely on public information, urges RAs to be more conservative in assigning shadow ratings. In addition, the study revealed that profitable and large banks operating in countries with high sovereign credit ratings are assigned high FBRs. On the contrary, low FBRs are assigned to banks with high loan loss reserve-to-gross loans ratios (i.e., poor asset quality) and high loans-to-total asset ratios (i.e., weak liquidity position). Finally, the results suggested that sovereign credit rating, bank size, profitability, asset quality, and liquidity are the most important determinates of FBRs.

Pasiouras et al. (2006), using 2004 data for a sample of 857 banks from 71 countries, examined the impact of bank regulations, supervision, market structure, and bank characteristics on FBRs. The method used was the order logit model. The findings revealed that the impact of bank profitability, liquidity, size and diversification of business and franchise power (expense management and asset quality) on FBRs are positive (negative) and statistically significant in all model specifications. The positive sign associated with predictor estimates indicated that large, profitable and more liquid banks with more subsidiaries are assigned higher FBRs. The negative sign implies that banks with lower asset quality (in terms of loan portfolio) and high cost-to-income ratio results in lower FBRs.

However, the impact of banks’ CS on FBRs is positive and statistically significant only when bank supervision and regulation framework variables are not included in the model. This indicates that well-capitalised banks are assigned higher FBRs. In addition, banks that are relatively more strictly controlled by institutional shareholders were found to obtain higher FBRs.

As for bank regulatory and supervisory variables, banks are assigned higher FBRs with higher deposit insurance power, liquidity and diversification guidelines, entry requirements, fraction of entries denied and economic freedom. High FBRs also are associated with banks in countries with lower capital requirements, official disciplinary power and no explicit deposit insurance scheme. In line with this, the results indicate that banks operating in restricted markets are assigned lower FBRs as greater restrictions on bank activities mitigate banking efficiency and development.

Concerning market structure variables, Pasiouras et al.'s (2006) results showed a positive (negative) relationship between the share of assets in foreign-owned banks (degree of asset concentration and share of assets in government-owned banks) and FBRs. This is mainly because greater government ownership increases banking sector fragility and financial system inefficiency. A piece of information that can be derived from this study is that banks operating in developed countries are assigned higher FBRs than those in emerging markets if regulatory and supervisory variables are not included in the model.

Godlewski (2007) also examined the coherence between bank default probabilities and Moody's BFSR and FBRs by employing a simple scoring and mapping technique and identifying the main determinants of bank ratings using logistic regression model. This paper used two samples of 483 and 257 banks for Moody's and Fitch respectively, located in emerging market economies (e.g., South-East Asia, South America and Central and Eastern Europe) during the period from 1998 to 2002.

The empirical results revealed that profitable, more liquid and well-capitalised banks with high reserves to cover nonperforming loans tend to have a low bank default probability and thus obtain a high Moody's BFSR. For the FBR sample, the empirical results of Godlewski (2007) revealed that banks with better capital adequacy, more total deposits-to-total assets ratio and a better cover of nonperforming loans with reserves results in lower bank default probability and thus higher FBRs. Using a simple scoring model, the results showed coherence between these ratings and actual bank default rates, although mapping results indicates that ratings tend to aggregate bank's default probability information into intermediate low category grade.

Pasiouras et al. (2007) used a sample of 153 South and South-East Asian commercial banks for the year 2004 to examine the possibility of predicting FBRs for Asian banks using publicly available data by employing a multigroup hierarchical discrimination technique. The dependent variable was FBRs (five rating scales). The independent variables included 10 financial and nonfinancial variables. Regarding financial variables, the empirical results revealed that banks with a high ratio of equity to customer deposit and borrowing (well-capitalised banks) and a high return on equity and net interest margin (profitable banks) tend to obtain high FBRs. As for nonfinancial variables, the number of institutional shareholders, the number of subsidiaries and the Heritage banking and finance score are the most important nonfinancial variables for FBRs.

A piece of information derived from this study is that regulatory restrictions on bank activity were found to have a negative and significant effect on FBRs, which is consistent with a recent study by Pasiouras et al. (2006). In line with this, the analysis also revealed that FBRs are significantly positively affected by the number of institutional shareholders and subsidiaries. Finally, the results highlighted that a multigroup hierarchical discrimination technique can predict FBRs with satisfactory classification accuracy (66.03%) in comparison to discriminant analysis (53.73%) and ordered logistic regression (47.55%).

Belloti et al. (2011a), using a sample of 681 international banks rated by Fitch and operating in 90 countries during the period from 2000 to 2007, examined the impact of financial variables and country risk on prediction of FBRs by using ordered choice estimation techniques and a support vector machine. The empirical results revealed that high FBRs are assigned to large, profitable and well-capitalised banks that operate in more stable/developed rich countries. In addition, highly liquid banks over the last two periods prior to the rating tend to obtain higher FBRs, and banks with high ratio of operating expense to total operating income tend to obtain lower FBRs. A piece of information derived from this study is that the inclusion of the country effect enhances the predictive performance of both the ordered choice model and the support vector machine and that the latter is substantially better than ordered choice models for in-sample predictive accuracy power.

Öğüt et al. (2012), using a sample of 17 Turkish banks covering the period from 2003 to 2009, predicted Moody's BFSR using the most important, publicly available, financial and operational variables. In addition, the authors examined whether or not the financial strength ratings produced by proposed prediction models in this study are consistent with those issued by RAs. For prediction purposes, two popular data mining techniques (i.e., support vector machine and artificial neural networks) were used and their results compared with two popular conventional techniques (i.e., multiple discriminant analysis and ordered logistic regression).

The empirical results of Öğüt et al. (2012) revealed that ordered logistic regression achieved the highest accuracy rate when using factor scores as input variables compared to other classifiers. On the other hand, the accuracy rates were the highest in multiple discriminant analysis and support vector machine when financial and operational variables were used as input variables. The results also indicated that the use of financial and operational variables, rather than using factor scores, as input variables improves the prediction accuracy rate. In addition, banks with high loan portfolios (loan-to-asset ratio and loan-to-deposit ratio), profitability (ROE), efficiency ratios (the ratio of net interest revenues [loss] to number of branches, the ratio of net interest revenue [loss] to total assets and the ratio of net interest revenue [loss] to number of employees) tend to obtain high BFSRs. A piece of information derived from this study is that RAs assign low ratings to banks that invest more of their funds (especially deposits) in government debt securities rather than selling loans. This is mainly because investment in government debt securities results in low profitability and high market risk (i.e., interest rate risk).

Hammer et al. (2012) constructed a reverse-engineering FBR model to evaluate the creditworthiness of 800 banks rated by Fitch and operating in 70 different countries as of December 2001. The main objective of the study was to predict FBRs accurately using a set of variables and to identify the main bank characteristics associated with high versus low FBRs. In addition, the authors developed a model to discriminate between high and low bank ratings in which the discriminant values are utilised to identify an accurate and predictive bank rating system. The methods employed in this study were multiple linear regressions, ordered logistic regression, support vector machine and logical analysis of data.

The empirical results of Hammer et al. (2012) revealed that the logical analysis of data and ordered logistic regression are better than multiple linear regression and support vector machine in providing the most accurate results in reverse-engineered Fitch bank-rating system. The results also revealed that the classification accuracy associated with logistic analysis of data outperformed that of ordered logistic regression. Consequently, the logical analysis of data approach is suitable for reverse-engineering bank rating as it is an objective, transparent and generalisable approach. These features can help bank mangers to construct internal rating systems that act in accordance with the IBR requirements and are consistent with Basel II requirements.

Shen et al. (2012) examined the influence of information asymmetry on RAs in assigning S&P's long-term credit ratings to banks operating in 86 countries from different regions during the period from 2002 to 2008 using similar financial ratios. This study divides the sample countries into high income or industrial countries with low information asymmetry and middle income or emerging countries with high information asymmetry. The method applied in this study was an ordered probit model.

The empirical results of Shen et al. (2012) revealed that banks with high capital, liquidity and profitability tend to obtain high ratings. Banks also tend to receive high ratings when they have high efficiency and high asset quality measures. The results also showed that large banks located in countries with high sovereign credit ratings tend to receive high bank credit ratings. The authors concluded that RAs assign greater weight to banks' financial ratios in high income or industrial countries because of low information asymmetry, better institutional environmental quality and high quality financial statements. However, the weight of banks' financial ratios was minimal in middle-income countries because of lack of transparency, high information asymmetry and low quality financial statements. A piece of information derived from this study is that enhancements in bank ratings are associated with countries that have low information asymmetry.

The relevant literature discussed above demonstrates a significant association between bank ratings and financial/nonfinancial characteristics across different regions using different RAs' bank ratings. However, this dimension has not been studied extensively for the Middle East region and the relationships between bank financial/nonfinancial variables and FSRs issued by CI have not been examined at all for the Middle East. This emphasises the importance of the current thesis in addressing this research gap. Appendix A summarises the relevant studies in the literature.

2.6 Financial sector in the Middle East region

In the last few decades, repressive policies have been adopted by various countries in the Middle East region (excluding Gulf countries) to stay in control of the money supply. These policies also serve some social goals, such as protection of financial institutions against usury practice by keeping the interest rates lower than the market rates to support the government debt at a lower cost. Such policies have forced banks to increase their reserve requirements, raise their credit ceilings and use selective credit allocation. This resulted in the development of a non-competitive and segmented financial sector. This forced Middle Eastern countries to adopt a financial reform agenda with the goal being to select better investment opportunities to improve productivity, mobilise savings, improve corporate governance and allow the trading, hedging, and diversification of risk (Naceur and Omran 2011). In the 2000s, some countries in the region, especially the Gulf Cooperation Council (GCC) countries, have begun to concentrate their efforts, using privatisation, enhancements of bank regulations and market orientation, with the goal of producing a well-developed, profitable and efficient banking sector.

In the late 1990s, the Middle East region was considered a bank-based economy, with banks controlling most financial activities. This forced many countries to adopt comprehensive banking sector reforms. Before this, most of the banking sectors in the Middle East were highly regulated and controlled mainly by governments. The prudential rules and regulations imposed by the governments were initiated mainly to mitigate the economic downturns associated with financial crises and to reduce adverse budgetary consequences for governments. In other words, the main purpose of such severe rules was to enhance the ability of bank management to make wise investment decisions (Murinde and Yaseen, 2004).

In line with the recommendations of the BCBS, the central banks recommended that banks raise their minimum capital requirement to 8%. In the same context, many countries in the region formulated bank laws that focus mainly on the transparency and disclosure of their central banks' activities. Central banks' most important activities can be summarised as follows: (1) issuing banknotes, (2) maintaining price stability, (3) managing gold and foreign exchange reserves, (4) preparing monetary, credit and banking policies, (5) supervising policy implementation, (6) supervising the national payment system, (7) recording and following up external debt (public and private), and (8) making recommendations to the government regarding loans and credit facilities.

GCC banks tend to be family-owned with a moderate amount of state ownership and participation. Accordingly, prudential guidelines were enacted by the GCC to regulate the launch of new banks in these countries and to reduce the probability of the failure of the banking sector. The guidelines cover such aspects as capital, capital reserves, a minimum age of 10 years for a bank, licensing, monitoring licensed foreign banks, bank closures, and a minimum capital retention requirement, among others (Jabsheh, 2002). The Middle East is described in the literature as having bureaucratic and political problems, underdeveloped financial markets, accrued opacity within the banking industry, a massive volume of nonperforming loans, and an inadequate regulatory, institutional and legal environment (Godlewski, 2005).

Therefore, it can be concluded that the rating of banks is a significant issue in the region. FSRs assigned by CI are used as an indicator of bank performance and strength. Thus, it would be of great benefit to economists and policymakers to determine the main quantitative factors that affect the rating assignment process and in particular the main financial and nonfinancial variables that produce high- and near-high FSRs and thus a better and more developed banking sector in the region. It has already been noted that RAs do not publish their rating methodologies, and thus it is unclear to the public why some banks are assigned a AAA rating and others a CCC rating. This thesis contributes to the attempt to remove this gap between practitioners and the public.

2.6.1 Banking industry in developing versus developed economies

In developing economies, the banking industry has different features than that in developed ones. This is mainly because the implications of either IRB or standardised approaches result in higher capital requirements in developing compared to developed economies. The reason is clear: the credit quality and credit ratings assigned to corporate borrowers in developing economies are considerably lower than those of developed economies. In addition, developing economies face difficulties in implementing IRB approaches because the new standards have not been adjusted for the environment in these economies. Thus, the standardised approach could be more suitable in this case, though it will not be effective because of the small number of RAs specialised in issuing ratings for corporate borrowers in this region.

In addition, Rojas-Suarez (2001) identified that the main problem facing developing markets is inefficient capital regulation rules that result from a lack of data, inadequate accounting standards and rules, bad reporting systems and inefficient financial markets. The author concluded that financial ratios are more relevant in industrialised countries than in developing markets for credit-rating explanation. The message of this discussion is that Basel II will increase capital charges in developing markets. This highlights the significant importance of bank FSRs in these markets as financial institution creditworthiness is a crucial prerequisite for financial system stability (Shen et al., 2012). It is possible that banks operating in developed markets may reduce lending to banks in developing markets with tight requirements (Griffith-Jones and Spratt, 2001). Nevertheless, lending decisions by banks in developed markets may be based more on economic capital rather than on regulatory capital (Jackson et al., 2002). In line with this, the market discipline exerted by RAs is an essential element in the interbank swap market where banks strive to maintain a cushion of capital above the regulatory capital requirement.

2.6.2 Banking sector in the Middle East region

The banking sector in the member countries of GCC witnessed remarkable developments during the 1970s and the first half of the 1980s. This was mainly a result of the outstanding boost in income per capita and saving capacity in these countries as a result of the oil boom. Financial deepening also has increased substantially in these countries. The acceleration of economic activity and banking development in line with progressive reform efforts are the main drivers in this regard. However, it should be noted that banks in the region face many common challenges that might hinder their ability to operate effectively and grow within a more competitive environment.

One of these challenges stems from overdependence on oil and the dominance of the public sector, which results in banks operating in over-banked, limited and often recessionary domestic markets. In addition, the investment opportunities are concentrated in specific sectors (e.g., real estate, trade and stock market activities). This in turn directs and limits bank lending to consumer loans, construction and trade finance. Moreover, banks in the GCC region are overprotected from foreign competition and deposits are entirely guaranteed by the government. This is unhealthy. It creates a fragile, inefficient banking sector.

GCC governments, within the progressive reform and liberalisation efforts and attempts around the world, have been forced to liberalise many financial services, including banking. The entry of foreign banks into the region with competitive pressures on domestic banks is among the main features of such a new era. The World Trade Organization and other international organisations are imposing pressures on GCC banks to adopt international standards for capital adequacy, risk management and accounting practices. Moreover, the government role as a lender of last resort for troubled banks in the region starts to lessen, creating additional competitive pressures across banks (Limam, 2001). Finally, the emergence of large investment companies represents another challenge faced by GCC banks.

For non-oil countries in the Middle East region, the structure of the banking sector can be illustrated as follows: The Egyptian government owns around 67% of the country's total banking assets, meaning that Egypt has the highest percentage owned by the state (Naceur and Omran, 2011). Jordan and Lebanon, meanwhile, have no banks owned by the government.

2.7 Rating agencies

This section provides an overview of major RAs, including Standard & Poor's, Moody's, Fitch and CI. For each RA, an historical background is given and different rating products with different maturities are illustrated. This section concludes with a comparison between long/short ratings scales across different RAs.

2.7.1 Standard & Poor's

Standard & Poor's (S&P) has been a leading agency since 1860 that provides analytical and research services across a range of publicly issued debt obligations. Independence, objectivity, creditability and disclosure are its core principles. S&P's credit rating and symbols are divided into issue-specific credit ratings and issuer credit ratings.

S&P's issue-specific credit ratings express an opinion about the creditworthiness of an obligor with respect to a specific financial obligation, a specific class of financial obligation or a specific financial program (e.g., bank loan or a debt issue). Such an opinion is based on three main considerations: the chances of obligor payment to meet its financial commitments in accordance with obligation terms, the nature of and provisions of the obligation and protection afforded by the obligation in the event of default or bankruptcy. S&P’s issuer credit ratings express an opinion about the obligor’s capacity and willingness to meet specific financial commitments at their due times. The word *specific* does not refer to any particular financial obligation, given that the nature and provisions of an obligation, its standing in bankruptcy or liquidation, statutory preferences or the legality and enforceability of the obligation are not considered issue-specific credit ratings (Standard and Poor's Ratings Services, 2013).

S&P’s credit analysts study both quantitative and qualitative aspects to determine corporate credit ratings. The overall company rating derives from both the overall, qualitative business-risk rating (i.e., industry characteristics, competitive position and management are the main determinants) and the overall quantitative financial-risk rating (i.e., financial policy, profitability, financial flexibility, CS and cash flow protection are the key factors). The issuance of bank rating is based on evaluation of the bank’s overall financial and business risks employing the so-called *bank rating analysis methodology profile*. The overall bank rating is derived after an examination of the five business risk factors (i.e., economic risk, industry risk, market position, diversification and management and strategy) and the six financial risk factors (i.e., credit risk, earning, liquidity and funding, market risk, capitalisation and financial flexibility) that affect overall bank performance.

To gather, analyse and process information about current and anticipated events and circumstances, S&P uses two rating scales within two time frames: the long-run (i.e., more than one year) and the short-run (i.e., one year or less). The long-run credit ratings result from an assessment scale that includes two scores: investment score (i.e., the safest level of financial securities with low default rates: AAA, AA, A and BBB) and speculative score (i.e., the riskier securities with relatively high default rates: BB, B, CCC, C, SD and D). It is worth mentioning that the S&P rating agency adds a plus (+) or a minus (-) to ratings AA to CCC to indicate the strength and weakness within a rating for every issuer. The short-run ratings are denoted by the symbols A-1+, A-1, A-2, A-3, B and C. The investment score is applicable only to A categories. The remaining categories are considered to be speculative scores.

S&P developed the so-called *CreditWatch listing* to monitor a list of issuers whose ratings may change when an event or deviation from an expected trend occurs or is expected. CreditWatch designation may be *positive*, meaning improved rating, or *negative*, meaning that the rating has deteriorated. Finally, S&P unsolicited ratings are based on an analysis of publicly available information sources such as a company's published annual report (Standard and Poor's Ratings Services, 2012b).

2.7.2 Moody's

Moody's is currently a freestanding agency that is highly specialised in credit rating. Moody's rating depends on a combination of both quantitative and qualitative criteria rather than purely quantifiable and objective criteria. Peer group analysis is an analytical technique used by Moody's to assess issuers' access to markets. This technique helps to identify the precise differences in the peer group or industry sector, which in turn enables the accumulation of knowledge and identification of possible discrepancies in the evaluation.

As with S&P, Moody's uses two rating scales within two time frames: the long-run (for specific issue and for issuer) and the short-run. Moody's long-term issuer ratings reflect opinions about the issuer's ability to satisfy senior, unsecured financial obligations denominated in foreign or/and domestic currency. The long-run ratings reveal both the default probability of an issuer and the amount of loss that may result from a default. Similar to S&P, Moody's rating scale includes two scores: (1) the investment score (Aaa, Aa, A and Baa represent the top four categories, with Aaa being the highest score). The highest investment score is assigned to well-insured issuers, even if they face severe economic conditions; and (2) a speculative score, which ranges from Ba (moderate threshold between good and bad credits) to C (bottom score reflecting very bad credit with poor investment prospects). It is worth mentioning that Moody's rating agency appends numerical modifiers 1, 2, or 3 to each generic rating classification from Aa through Caa. The modifier 1 indicates that the obligation ranks at the higher end of its generic rating category; the modifier 2 indicates a mid-range ranking; and the modifier 3 indicates a ranking in the lower end of the generic rating category (Moody's Investors Service, 2013).

Moody’s short-run ratings deal with securities that mature in less than one year. In this context, Moody’s classifies issuers as those who may not be able to meet their entire short-term obligations (NP: not prime) and those for whom the possibility of meeting their obligations is high (P: prime). Within P, there are sub classifications (P-1: highest degree of investor protection; P-2: moderate protection; P-3: lowest protection).

Moody’s BFSR was inaugurated in 1995 and is available on a solicited and unsolicited basis for banks from 50 countries. BFSRs are a common way to judge bank safety and soundness, and they correspond to Moody’s opinion on a bank’s internal financial strength (i.e., the probability that a bank will require assistance from third parties such as owners, industry groups or government institutions such as the central bank).

Before assignment of BFSRs, Moody’s analyses five quantitative and qualitative factors: franchise value, risk positioning, regulatory environment, operating environment and financial fundamental . According to Moody’s, franchise value measures the ability of banks to survive in a given geographical market or business niche. This measure includes a bank’s market share and sustainability, geographical diversification, earning stability and diversification and ability to overcome events that can destroy a bank’s franchise value. The second factor, risk positioning, defines a bank’s risk behaviour and its risk-management approach. This factor accounts for corporate governance, controls, financial reporting transparency, credit risk concentration and liquidity management. The third and fourth factors (i.e., regulatory and operating environment) are general factors concerned mainly with the environment in which the bank operates. The fifth factor encompasses financial fundamentals such as profitability, liquidity, capital adequacy, efficiency and asset quality.

The rating scale ranges from A banks (exceptional intrinsic financial strength, strong financial fundamentals and attractive stable operating environment) and E banks (weak financial fundamentals, unattractive operating environment and a severe need for periodic outside support). Between these two ends, B, C and D banks exist on the scale. A plus (+) modifier is appended to ratings below the A category and a minus (-) modifier is appended to ratings above the E category to distinguish those banks that fall in intermediate categories. Moody’s also has developed *rating outlooks* and a *rating review/watch list* as periodic judgements of good (poor) performers in terms of the above-mentioned scales(Moody's Investors Service, 2013) .

2.7.3 Fitch

Fitch is a leading global rating agency and is regarded by some people as a main competitor of the US duopoly of Standard & Poor’s and Moody’s. Fitch supplies the word’s credit market with independent and prospective credit opinions, research and data (e.g., Bankscope database). Leadership, responsiveness, transparency and perspective are the core principles of Fitch’s rating system. Fitch has been mainly developed by strategic mergers and acquisitions, which may explain the rapid growth of Fitch during the past decades.

Fitch ratings activities are spread globally to cover sovereign, financial, bank, insurance, municipal and other public finance entities and the securities or other obligations they issue.

A merger between Fitch and Thomson Bank Watch in December 2000 strengthened Fitch's position in the business of bank ratings. With more than 1,000 international bank ratings, Fitch is considered to be the leading bank credit rating agency in terms of coverage with its main concentration in the emerging markets (e.g., Asia, Africa and Middle East, Central and Eastern Europe and Latin America). Fitch's market share for bank ratings in emerging markets is almost twice that of S&P's and Moody's.

Fitch ratings are classified into international and national. Simply, international credit ratings access the capacity to meet foreign currency or local currency commitments; whereas national credit ratings are assessments of credit quality relative to the rating of the best credit risk in a country. In line with this, Fitch covers four major kinds of credit rating: long-term credit rating, short-term credit rating, FBR, and bank support rating. As with the other rating agencies, *long-term credit rating* and *short-term credit rating* have the same meanings, which are interpreted as an opinion about the ability of an entity to meet financial obligations (interest, preferred dividends or repayment of principle) on a timely basis.[32] Consequently, Fitch's long-term credit rating scale includes two scores. In line with S&P's ratings, the first is the investment score (AAA, AA, A and BBB represent the top four categories, with AAA being the highest score). The second is speculative score (i.e., the riskier securities with relatively high default rates; BB, B, CCC, CC, C, RD and D). To denote relative status within major rating categories, the plus (+) or minus (-) modifiers are attached to ratings from AA to B. The short-term credit rating scores are denoted by the symbols F-1+, F-1, F-2, F-3, B and C. The investment score is applicable only to F categories. The remaining categories are considered to be speculative scores.

[32] Short-term rating has a time horizon of not more than 12 months for most obligations.

FBRs, recently known as bank viability ratings, are used mainly to assess banks' quality and strength without any external support. The FBR represents Fitch's opinion about the possibility that a bank may face significant difficulties that would necessitate immediate support. The main factors that determine these ratings include profitability and balance sheet integrity (including capitalisation), franchise, management, operating environment, size (in terms of equity capital), diversification (in terms of involvement in a variety of activities in different economic and geographic sectors) and prospects. FBR scores range from A denoting for a very strong bank to E, which indicates a bank with very serious problems that require external support. Between these two ends, A/B, B, B/C, C, C/D, D and D/E ratings exist on the scale (Fitch Ratings, 2013).

Bank support ratings comprise five rating categories and represent Fitch's opinion about the potential tendency of a supporter (either the governmental authorities or institutional owners) to support a bank in distress periods. Assignment of such ratings is based on four broad categories of criteria: guarantees and commitments, percentage control, nature of the owner and importance of the bank to the owning institution. Support rating scores vary from 1, which denotes a high probability of external support. This is backed by two main reasons: (1) supporter's high propensity to support the bank and (2) the supporter is itself very highly rated. The other extreme of scoring is represented by 5, for which the expected external support for the bank is in great doubt. Finally, it is worth mentioning that Fitch developed the *Rating Watch* and *Rating Outlook* as equivalent lists developed by RAs discussed previously.

2.7.4 Capital Intelligence (CI)

CI is one of the most specialised rating agencies[33] in the Middle East region. CI has provided ratings services since 1985. Strong professionalism in providing valuable information to banks' creditors about banks' financial strength distinguishes CI from other RAs. Also, CI enjoys a good reputation in the qualitative and quantitative analysis of banks (i.e., mainly profitability and capital adequacy). The independence, objectivity and analytical consistency have enabled CI to expand the scope of its rating services to include corporate credit, bonds and other financial obligations. The rating process for CI starts with an examination of the traits of a country's banking system by evaluating the regulatory and supervisory regime as well as the accounting and auditing practices of the relevant market. In this regard, it should be highlighted that CI uses a comprehensive list of evaluation ratios and factors (country-, market-, institutional- and bank-level) (Capital Intelligence, 2012).

CI ratings are classified as international or national. According to Capital Intelligence (2011), international credit ratings are classified into issuer credit ratings (which measure the creditworthiness of an entity, sovereigns, financial institutions and corporate entities, and its ability to meet its financial obligation in a timely manner) and issue-specific credit ratings (an opinion about the willingness of an a financial institution or a corporation to satisfy its financial obligations with respect to a specific bond or other debt instrument). CI uses two rating scales within two (long-term and short-term) time frames. The issuer credit ratings are categorised into foreign and local currency ratings, which assess the willingness and ability of an entity to satisfy financial obligations denominated in foreign (local) currency, controlling for economic, financial, country risks and external support. In the case of foreign currency

[33] CI's geographical coverage includes the Middle East, the wider Mediterranean region, Central and Eastern Europe, South Africa, South East Asia, the Far East and North and South Africa.

credit ratings, restrictions imposed by governments on foreign exchange are taken into account.

CI has developed two additional ratings for financial institutions: (1) an FSR, which assesses the bank's intrinsic financial strength, soundness and risk profile, controlling for many factors related to the operating environment; and (2) support ratings, which emphasise the probability that banks would receive support from third parties in case of difficulties. The rating scale applied to the FSR is the same as for foreign and local currency ratings. The rating scale applied to support ratings ranges from 1 (a bank that has a high probability of receiving financial assistance in the event of difficulties because of the extremely strong ability and willingness of potential supports to provide sufficient and timely support) to 5 (the likelihood of support is low). Tables 2.2 and 2.3 summarise the major rating categories for S&P, Moody's, Fitch and CI.

Table 2.2: Long-term ratings/scales for the four rating agencies

S&P	Moody's	Fitch	CI
Investment Score			
AAA	Aaa	AAA	AAA
AA	Aa	AA	AA
A	A	A	A
BBB	Baa	BBB	BBB
Speculative Score			
BB	Ba	BB	BB
B	B	B	B
CCC	Caa	CCC	C
CC	Ca	CC	
C		C	
Default			
SD, D	C	RD, D	RS,SD,D

Source: Developed by the researcher

Table 2.2 summarises and compares the long-term ratings/scales issued by the four rating agencies. AAA is the highest credit rating assigned by S&P. This rating refers to the highest level of financial creditworthiness and strong commitments. The AA rating is slightly below the AAA rating. The A rating refers to strong but unsustainable financial creditworthiness.

The position of the obligor in this case may be easily affected by adverse shocks and significant changes in economic conditions. The obligors in higher rated categories may have more capacity to adjust their positions in response to adverse shocks. BBB refers to a reasonable capacity to meet financial commitments.

BB refers to a low level of creditworthiness associated with different sources of uncertainties. B is below BB and refers to weak financial commitments. CCC comes after B and denotes a high degree of vulnerability and fragile financial position. CC means that the obligor is in financial stress with the possibility of bankruptcy. A C rating points to bankruptcy, although debt service payments continue. The SD (selective default) rating is assigned when S&P considers that the issuer has selectively defaulted on a specific issuer or class of obligations when they are due. D is among the worst ratings and is assigned when the obligor fails to meet all or substantially all of its obligations. Ratings ranging from AA to CCC are adapted by the addition of a plus or minus sign to show relative standing within the major categories (Standard and Poor's Ratings Services, 2013).

Moody's Aaa rating refers to entities with strong positions that may enable them to offer exceptional financial security. Aa is below Aaa and implies a possibility of long-run risk. An A rating refers to good financial security, though the possibility of long-run risk is greater than for those rated as Aa. Baa lags behind A such that the issuers may offer adequate financial security with weak or unreliable protective elements.

Ba refers to so-called risky issuers with weak commitments. Below Ba, the B rating refers to riskier issuers, poor financial security and questionable credibility. Generally speaking, the Caa rating is designed to refer to issuers who have strong incentives to evade/default on their obligations. Ca refers to issuers with on-going default on their obligations. The element of trust could be missing from Ca rated issuers. C is the lowest-rating and is used for issuers who are characterised by long-run default and very weak possibilities of recovery. Ratings ranging from Aa to Caa are adapted by the addition of the modifiers 1, 2 and 3 to show relative standing within the major categories (Moody's Investors Service, 2013).

Fitch’s AAA rating indicates the highest credit quality with the lowest risk. This is usually assigned to entities with extended strong financial positions and credibility. AA is slightly below AAA. Although an A rating represents high credit quality, it may refer to a higher degree of risk and vulnerability than AAA and AA ratings. The B class of ratings indicates an increased degree of expected risk. Below the BBB and BB ratings, a B rating refers to significant credit risk with a limited safety margin and questionable long-run commitments. The C class of ratings refers to possibilities of default, with CCC as the highest (default is expected) and C as the lowest (default is imminent). The RD (restricted default) rating means that the issuer has selectively defaulted on a specific issue but will continue to meet its payment obligations in a timely manner. Finally, the D rating is designed to include entities that have defaulted on all of their financial obligations. Ratings ranging from AA to B are adapted by the addition of a plus (+) or minus (-) sign to show relative standing within the major categories (Fitch Ratings, 2012).

Finally, CI’s A class of ratings is very similar to that of the preceding ratings. The same applies to the B class, in which, for example, BBB represents the high credit quality, BB represents speculative qualities associated with some vulnerability and the B rating refers to significant credit risk and uncertainty. Below the B class, a C rating refers to sizeable risk and strong default possibilities. Like S&P’s, the SD (selective default) rating is assigned when CI considers that the issuer has failed to service one or more financial obligations when it came due but believes the issuer will be able to satisfy other financial commitments in a timely manner. The RS (regulatory supervision) rating is issued specifically for financial institutions and means that the issuer is under the regulatory supervision of the authorities because of its poor financial condition. Finally, the lowest rating, D, represents defaulted cases. The same applies to FSRs, in which, for example, the A class of ratings represents CI's opinion about banks with strong financial positions and that the operating environment is attractive and stable. Ratings ranging from AA to C are adapted by the addition of a plus (+) or minus (-) sign to show relative standing within the major categories (Capital Intelligence, 2011).

Table 2.3: Short-term ratings/scales for the four rating agencies

S&P	Moody's	Fitch	CI
Investment Score			
A-1+	P-1	F-1+	A1
A-1		F-1	A2
A-2	P-2	F-2	A3
A-3	P-3	F-3	
Speculative Score			
B	NP	B	B
C		C	C
Default			
SD/D	NP	RD/D	RS/ SD/ D

Source: Developed by the researcher

For the short-term ratings shown in Table 2.3, for S&P, A-1 means that an obligor has a strong capacity to meet its financial commitments; certain obligors are designated with a plus sign (+), which indicates that the obligor's capacity to meet its financial commitments is extremely strong. A-2 means that an obligor has satisfactory capacity to meet its financial commitments. However, it is somewhat susceptible to the adverse effects of changes in circumstances and economic conditions than obligors in the highest rating category. A-3 means that an obligor has adequate capacity to meet its financial commitments. However, adverse economic conditions and changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.

A B rating means that the obligor is regarded as vulnerable and has significant speculative characteristics. The obligor currently has the capacity to meet its financial commitments; however, it faces major on-going uncertainties that could lead to the obligor's inadequate capacity to meet its financial commitments. A C rating means that the obligor is currently vulnerable to non-payment and is dependent upon favourable business, financial and economic conditions for it to meet its financial commitments. The SD (selective default) indicates that am obligor has defaulted in one or more of its financial commitments. A D rating means that the obligor is in payment default (Standard and Poor's Ratings Services, 2012b).

Moody’s P-1 rating means that issuers have superior ability to repay senior short-term debt obligations. P-1 repayment ability will often be evidenced by many of the following characteristics: leading market position in well-established industries, high rates of return on funds employed, conservative capitalisation structure with moderate reliance on debt and ample asset protection, broad margins in earnings coverage of fixed financial charges and high internal cash generation and well-established access to a range of financial markets and assured sources of alternate liquidity.

A P-2 rating means that issuers have a strong ability to repay senior short-term debt obligations. This is normally evidenced by many of the characteristics cited above but to a lesser degree. Earnings trends and coverage ratios, although sound, may be more subject to variation. P-3 means that issuers have an acceptable ability to repay senior short-term obligations. The effect of industry characteristics and market compositions may be more pronounced. Variability in earnings and profitability may result in changes in the level of debt protection measures and may require relatively high financial leverage. NP means that the issuers do not fall within any of the prime rating categories (Moody's Investors Service, 2013).

For Fitch rating, F1 denotes the highest credit quality and the strongest capacity for timely payment of financial commitments. An added plus sign (+) is ued to denote any exceptionally strong credit feature. F2 denotes good credit quality and a satisfactory capacity for timely payment of financial commitments, but the margin of safety is not as great as in the case of the higher ratings. F3 denotes fair credit quality in which the capacity for timely payment of financial commitments is adequate; however, near-term adverse changes could result in a reduction to a noninvestment grade.

A B rating represents a speculative stage. This rating denotes minimal capacity for timely payment of financial commitments, plus vulnerability to near-term adverse changes in financial and economic conditions. A C rating means a high default risk in which default is a real possibility. Capacity for meeting financial commitments relies solely on a sustained, favourable business and economic environment. The RD (restricted default) rating denotes that an entity has defaulted on one of its financial obligations, although it continues to meet other financial commitments. A D rating indicates an entity or sovereign that has defaulted on all of its short-term financial obligations (Fitch ratings, 2012).

Similar to agencies discussed previously, CI's A1 means superior credit quality and represents the highest capacity for timely repayment of short-term financial commitments such that unexpected adversities are extremely unlikely to pose a threat. A2 represents a very strong capacity for timely repayment of short-term financial commitments but that the issuer may be affected slightly by unexpected difficulties. A3 represents a strong capacity for timely repayment of short-term financial commitments that may be affected by unexpected difficulties.

A B rating represents an adequate capacity for timely repayment of short-term financial commitments that could be seriously affected by unexpected difficulties. A C rating represents an inadequate capacity for timely repayment of short-term financial commitments if unexpected difficulties are encountered in the short term. RS (regulatory supervision; this rating is assigned to financial institutions only) indicates that the obligor is under the regulatory supervision of the authorities because of its weak financial condition. The likelihood of default is extremely high without continued external support. SD means selective default, in which the obligor has failed to service one or more financial obligations but CI believes that the default will be restricted in scope and that the obligor will continue to pay other financial obligations at their due time. A D rating represents a weak position in which the obligor has defaulted on all, or almost all, of its financial commitments (Capital Intelligence, 2011).

2.8 Conclusion

A critical review of the literature leads to the conclusion that banks are special and their unique and opaque characteristics, functions, operations, regulations, asset structures, involved risk and state protection laws necessitate special rating methodologies. The determinants and prediction of bank ratings are extensive and well established for developed economies compared to developing economies, including the Middle East region. Thus, one objective of this thesis is to determine the main quantitative factors that affect the rating assignment process and, in particular, the main financial and nonfinancial variables that produce high- and near-high FSRs that lead to better and more developed banking sectors in the Middle East region.

Additionally, a model to discriminate between high and low FSRs through which the discriminant values are utilised to identify an accurate and predictive bank rating system is developed. In terms of estimation techniques, and to the best of the researcher’s knowledge to date, the researcher is not aware of other studies relative to the Middle East that address the use of conventional and machine-learning techniques for predicting bank FSR group memberships. The following chapter presents the research methods used in this study.

CHAPTER 3 : METHODOLOGY AND DATA COLLECTION

3.1 Introduction

This chapter describes data and techniques used in this thesis. The first section discusses the data collection procedure and explains the dependent variable (i.e., bank FSRs) as well as the main independent and control variables used in this study. The second section describes the main statistical techniques employed. The researcher applied the ML technique to identify the main financial and nonfinancial variables associated with high- and near-high FSRs versus low- and near-low FSRs in the Middle East region. This is to satisfy one of the main objectives of this thesis.

Another objective is fulfilled by using two conventional techniques, namely DA and LR, and three machine-learning techniques (CHAID, CART and MLP neural networks) to discriminate and predict bank FSR group membership for banks located in the Middle East region. The procedure for the selection of such predictive models and the usage of different evaluation criteria are explained thoroughly in subsections that follow.

It is worth mentioning here that this thesis reflects the philosophy of a positivistic approach that adopts the philosophical stance of the natural scientist. Positivism usually starts with testable hypotheses (as mentioned earlier) extracted mainly either from speculative theories or gaps in the empirical literature. This approach depends entirely on application of different statistical techniques to a large set of quantitative data to test designated hypotheses, the results of which may bridge the gap found in the literature.

3.2 Data and research methods

This section addresses (1) data collection, (2) dependent variable and rating categories, (3) independent variables and expected signs with bank FSR, and (4) control variables.

3.2.1 Data collection

The overall sample consists of 135 active commercial banks in the Middle East region. The researcher focuses only on commercial banks to avoid comparison problems between various types of banks and to provide homogeneity in the comparison between countries. Banks are from 10 countries in the Middle East region[34], as shown in Table 3-1, and the data are from 2001 to 2009.

The data were obtained from Bank scope database of Bureau van Dijk.[35] Bank scope contains financial statements and data on more than 11,000 public and private banks worldwide. The rationale behind the use of the Bank scope database is that it presents banks' financial information using a separate data template for each country thus allowing for differences in reporting and accounting conventions. In addition, the Bank scope database converts data into a global format, resulting in standard financial ratios that can be compared across banks and countries (Pasiouras et al., 2006). The number of commercial banks rated by CI in the Middle East region is only 64 banks and the remaining 71 banks have not been rated.

The researcher divided the data set into three samples. The first sample includes the entire data set (351 observations). The researcher has removed bank observations with missing data from the entire data set to enhance explanatory, discriminatory and predictive models' quality. The second sample includes subsample$_1$ (67% training sample; 235 observations and

[34]Israel, Palestinian Territory, Iraq and Syrian Arab Republic are excluded from the sample because they do not have commercial banks rated by CI. Iran is also excluded from the sample as all Iranian banks are Islamic according to Bank scope database classification.
[35] Note that the top three RAs (Moody's, S&P's and Fitch) as well as CI and the Economic Intelligence Unit issue rating reports for Bank scope.

33% testing sample; 116 observations). The researcher has selected randomly both training and testing subsample$_1$ using PASW® Modeler 14 software. The third sample includes subsample$_2$ (2001-2006 training sample; 235 observations and 2007-2009 testing sample; 116 observations). The entire data set was used as a test set to examine the overall predictive capability of the proposed classification models because of the benefits of a large data set. The researcher developed subsample$_1$ and subsample$_2$ as a simple validation technique that tests the predictive effectiveness of the fitted model.

Table 3.1: Descriptive statistics for banks, by country and whether rated by CI, based on bank size (in total assets)

Country	# Active Commercial Banks	# Banks with CI's FSR	% of Banks Rated by CI	Mean Size (Total Assets)	Standard Deviation (Total Assets)
Bahrain	10	4	40	9.422	0.819
Egypt	24	6	25	8.809	0.855
Jordan	11	7	63.6	7.433	1.296
Kuwait	6	6	100	9.231	0.598
Lebanon	38	6	15.7	8.688	0.708
Oman	6	5	83.3	7.810	0.708
Qatar	8	4	50	8.547	1.146
Saudi Arabia	9	9	100	9.672	0.815
United Arab Emirates[36]	18	15	83.3	8.248	1.316
Yemen	5	2	40	5.832	0.554
Total	135	64	47.4	8.521	1.308

Source: Developed by the researcher

Table 3.1 shows descriptive statistics for each country based on bank size (i.e., the natural log of total assets in US dollars). It is clear that banks in Saudi Arabia, Bahrain and Kuwait are larger in size than those in other countries. Meanwhile, Yemen's banks are smaller than those of other countries. Furthermore, banks in Egypt, Lebanon, Qatar and United Arab Emirates have a similar average size, as do banks in Jordan and Oman.

[36] Although the number of rated banks in the UAE seems different from other countries in the Middle East, this does not necessarily conclude a different banking regulatory environment. The common understanding in the related literature is that the GCC share common banking regulations. Nevertheless, the researcher further examines the country effect using dummy variables in the analysis.

3.2.2 Dependent variable

The dependent variable is bank FSR, which indicates CI vision of the bank's intrinsic financial strength, soundness and risk profile (the researcher examines the country risk profile using the sovereign rating as an efficient proxy that is well-known in the related literature). Bank FSRs are a categorical variable and an ordered relationship exists between them. However, econometric models employed in this thesis accept only numeric variables. For this reason, the rating scale is coded by assigning numerical values for each bank FSR score. The lowest rating (i.e., D) is assigned 1 and other ratings are increased by 1 when bank FSR improves by one grade.

This method is common in other relevant studies (Belloti et al., 2011a; Hammer et al., 2012; Öğüt et al., 2012; Pasiouras et al., 2006; Poon et al., 1999; Poon and Firth, 2005; Poon et al., 2009; Shen et al., 2012). The researcher found no banks in the Middle East with assigned ratings as high as AAA, AA+ and AA nor as low as B-, C+, C, C- and D during the period from 2001 to 2009. Using a simple weighted average, Table 3.2 shows the numerical ratings and the rating categories examined in this thesis.

Table 3.2: A synopsis of CI bank FSRs, numerical ratings and rating categories

CI's Bank FSR	Numerical	Categories
AAA	20	high FSR
AA+	19	
AA	18	
AA-	17	
A+	16	
A	15	
A-	14	near-high FSR
BBB+	13	
BBB	12	near-low FSR
BBB-	11	low FSR
BB+	10	
BB	9	
BB-	8	
B+	7	
B	6	
B-	5	
C+	4	
C	3	
C-	2	
D	1	

Source: Developed by the researcher.
Note. The ratings range from AAA (highest rating) to D (lowest rating). For ratings AA to C, CI adds a plus (+) or a minus (−) to represent the strength and weakness in a grade of rating for every bank.

In the first analytical stage, four quartiles were categorised into two groups to determine the main financial and nonfinancial variables associated with low- and near-low-FSR banks versus high- and near-high-FSR banks. In the second and third analytical stage, the first and fourth quartiles (corresponding to low FSRs and high-FSR banks) are only used to discriminate and predict bank FSR group membership. Bank FSR group membership is explained by two values, namely, high- FSR = 1 and low- FSR= 0.

3.2.3 Independent variables

This thesis examines the association between bank CS, financial and nonfinancial variables and bank FSR and discriminates and predicts bank FSR group membership using financial and nonfinancial variables. It is worth mentioning that Öğüt et al.'s (2012) empirical findings revealed that the accuracy rates of prediction classifiers are higher with the use of variables rather than factor scores. For that reason, the researcher used financial and nonfinancial variables rather than factor scores as input variables.

The equity ratio is a well-known proxy for bank CS. The literature provides evidence that this ratio avoids distortions in the measurement of capital structure, since this ratio measures the amount of protection afforded to the bank by the equity they invested in it (Poon and Firth, 2005). In addition, the researcher further argues that the use of equity ratios avoids a possible contradiction that may arise due to differences between short-term and long –term debt in the banking industry. The effects of bank CS on FSR also are influenced by other aspects or categories of bank performance. It is believed that bank asset quality, liquidity, profitability, credit risk and capital adequacy, as determined by CI[37], have an effect on bank FSR. Consequently, the main independent variables are bank CS and various financial variables of each of the above five categories of bank performance. The researcher studied the impact of each category on bank FSR as each category examines an independent bank activity. Each of the five categories includes various measures that are used to discriminate and predict bank FSR group membership. A detailed description of each measure is given in Table 3.3.

Table 3.3: List of bank financial variables examined[38]

Factors (Predictors of Bank Performance)	Variables (Ratio/Proxy)	Expected Relationship to Bank FSRs	Definition
Asset quality	Loan loss provision/Net interest revenue (LLPNIR)	Negative	The ratio of loan loss provision to net interest revenue denotes the relationship between provisions in profit and loss accounts and interest income over the same period. The estimated amount of provision reflects the expected amount of loans becoming non-performing, thus high provisions mean a higher percentage of nonperforming ratio, which indicates poor asset quality. Ideally, this ratio should be as low as possible. In a well-run bank, if the lending book is higher in risk, this is reflected by higher interest margins. If the ratio

[37]This is based on the CI classification.

[38] All definitions within the categories of asset quality, capital, operations and liquidity were obtained from the Bank scope database and CI website.

			deteriorates, this means that risk is not being properly remunerated by the margins.
	Loan loss reserve/Impaired loans (LLRIL)	Positive	The ratio of loan loss reserve to impaired loans or non-performing loans. Obviously, banks with high LLRILs are considered more conservative and thus investors will feel more comfortable about its asset quality.
	Impaired loans/Gross loans (ILGL)	Negative	The ratio of impaired loans to gross loans (loans + loan loss reserve). This ratio measures the proportion of total loans that are doubtful. In the 2000s, banks began to develop and implement advanced strategies and techniques to lower this ratio as much as possible to enhance their asset quality.
	Net charge off/Net income before loan loss provision (NCONIBLLP)	Negative	The ratio of net charge-off (amount written off from loan loss reserves less recoveries from loans) to net income before loan loss provisions is measured similarly to charge-offs but against income generated in the year. Intrinsically, bank asset quality improves when this ratio deteriorates, other things being equal.
	Impaired loans/Equity (ILE)	Negative	The ratio of impaired loans to equity.
	Unreserved impaired loans/Equity (UILE)	Negative	The ratio of unreserved impaired loans to equity.
Capital Adequacy	Tier 1 ratio (TR)	Positive	A comparison between a bank's core equity capital and its total risk-weighted assets mainly composed of Tier 1 capital (common stock and disclosed reserves or retained earnings plus sometimes perpetual non-cumulative preference shares) as a percentage of risk-weighted assets measured under Basel rules. This ratio is used mainly by regulators to grade bank capital adequacy as one of the following rankings: well-capitalised, adequately capitalised, undercapitalised, significantly undercapitalised, and critically undercapitalised. This ratio should be at least 4%; otherwise bank is considered to be undercapitalised.
	Total capital ratio (TCR)	Positive	The ratio of total capital (Tier 1 + Tier 2) to risk-weighted asset. The total capital ratio of a bank must be at least 8%. This indicates that 8% of the bank's risk-weighted assets must be covered by permanent or near permanent capital.
	Equity/Total assets (CS)	Positive	This ratio is used as a proxy for the bank's CS. This ratio measures the ability of the bank to withstand losses. A declining trend may signal increased risk exposure and possibly a capital adequacy problem.
	Equity/Net loans (ENL)	Positive	This measures the equity cushion available to absorb losses on the bank's loan book.
	Equity/Liabilities (EL)	Positive	This leverage ratio is another way to consider equity funding of the balance sheet and thus capital adequacy.
	Equity/Deposit and short-term funding (EDSF)	Positive	This ratio measures the amount of permanent funding relative to short-term, potentially volatile funding. The higher this ratio is, the better from the bank's risk perspective.

	Capital funds[39]/Total Assets (CFTA)	Positive	The ratio of capital funds to total assets. The capital funds include bank's equity plus hybrid capital plus subordinated debt.
	Capital funds/Net loans (CFNL)	Positive	The ratio of capital funds to net loans.
	Capital funds/Deposit and short-term funding (CFDSF)	Positive	The ratio of capital funds to deposits and short-term funding.
	Capital funds/Liabilities (CFL)	Positive	The ratio of capital funds to total liabilities.
	Subordinated debt/Capital funds (SDCF)	Negative	The ratio of subordinate debt to capital funds. This ratio indicates what percentage of total capital funds is provided in the form of subordinated debt.
	Equity multiplier (EM)	Negative	The ratio of total assets to total equity. This ratio measures how many times a dollar of equity is leveraged. A higher EM indicates higher financial leverage, which means the bank relies more on debt to finance its assets.
Profitability	Net interest margin (NIM)	Positive	This ratio is net interest income (interest revenue minus interest expense) expressed as a percentage of earning assets (loans plus other earning assets excluding fixed assets). The higher this ratio, the cheaper the funding or the higher the margin the bank generates. Higher margins and profitability are desirable as long as the asset quality is maintained.
	Net interest income/average assets (NIIAA)	Positive	This ratio measures the degree of bank efficiency in generating net interest income with available bank assets.
	Other operating income/Average assets (OIAA)	Positive	This ratio indicates to what extent fees and other income make up the bank's earnings. As long as this is not volatile trading income, it can be seen as a form of income with lower risk. The higher this figure is, the better.
	Non-interest expense/average assets (NIEAA)	Negative	This ratio gives a measure of the cost side (overhead plus loan loss provisions) of the bank performance relative to assets invested. The lower this figure is, the better.
	Pretax operating income/Average assets (PTOIAA)	Positive	This ratio is a measure of the operating performance of the bank before tax and unusual items (profits before tax plus other). It is a good measure of profitability that is unaffected by non-trading activities.
	Non-0perating items and taxes/Average assets (NOITAA)	Negative	This ratio measures costs and tax as a percentage of assets invested. The lower this figure is, the better.
	Return on average assets (ROAA)	Positive	The ratio of net income to average total assets. This ratio is perhaps the most important ratio in comparing the efficiency and operational

[39] This form of debt instrument has been substituted for equity and is a hybrid in the sense that it incorporates both debt and equity features and often includes specific option elements. The main objective of such instruments is to maximise the benefits of both debt and equity holders. Hybrid capital includes a variety of instruments, such as preference shares, that are not pure equity but have traditionally been deemed close enough to it to count toward a bank's Tier 1 capital ratio.

		performance of banks. This is mainly because it considers returns generated from assets financed by the bank.
Return on average equity (ROAE)	Positive	ROE is a measure of the return on shareholder funds (earnings performance). The higher this figure is, the better. However, care must be taken to avoid putting too much weight on this ratio as it may be at the expense of an over-leveraged bank.
Dividend pay-out (DPO)	Positive	This ratio measures the amount of after-tax profits paid to shareholders. In general, the higher the DPO, the better is bank profitability, but not at the cost of restricting reinvestment in the bank and its ability to grow its business.
Income net of distribution/Average equity (INODAE)	Positive	This ratio is effectively the return on equity after deduction of dividends paid from returns. It shows by what percentage the equity has increased from internally generated funds. The higher this figure is, the better.
Non-operating income/Net income (NOINI)	Positive	This ratio denotes the percentage of total net income that is made up of unusual items. This ratio is a proxy that measures bank revenue diversification.
Cost-to-income ratio (CIR)	Negative	The ratio of overhead to the sum of net interest revenue and other operating income. This is currently one of the most focused-on ratios as it is used as a proxy measurement of management ability to control expenses. That is, it measures management quality and overhead or costs of running the bank, the major element of which is staff salaries and benefits, rent expenses, equipment expenses and other administrative expenses, stated as a percentage of income generated before provisions. Thus, higher values of this ratio indicate less efficient management. Note that this ratio improves automatically if lending margins in a particular country are very high. Also, this figure can be distorted by high net income from associates or volatile trading income.
Recurring earning power (REP)	Positive	The ratio of pre-provision income to average total assets. This ratio is a measure of after-tax profits, including provisions for bad debts, as a percentage of average total assets. This measures ROA performance without deducting provisions.
Net profit margin (NPM)	Positive	The ratio of net income to interest income plus non-interest income. This ratio reflects the effectiveness of bank expense-control programs and service pricing.
Asset utilisation (AU)	Positive	The ratio of interest income plus non-interest income to total assets. This ratio measures how banks implement efficient management policies for bank portfolio decisions, especially the mix and yield of assets.
Tax management efficiency (TME)	Positive	The ratio of net income to pretax operating income. This ratio reflects bank usage of security gains or losses and other tax-management tools (such as buying tax-exempt bonds) to minimise its tax exposure.

	Expense control efficiency (ECE)	Positive	The ratio of pretax operating income to interest income plus non-interest income. ECE measures bank effectiveness in controlling operating expenses.
	Operating efficiency ratio (OER)	Negative	The ratio of interest expense plus non-interest expense plus provisions for loan losses plus taxes to interest income plus non-interest income plus securities gains (or losses).
Credit risk	Net charge-off/Average gross loans (NCOAGL)	Negative	This ratio represents the net charge-off (i.e., the amount written off from loan loss reserves less recoveries) measured as a percentage of gross loans. This ratio indicates what percentage of today's loans is written off the book. The lower this figure is, the better, as long as the write-off policy is consistent across comparable banks.
	Loan loss provisions/Total loans (LLPTL)	Negative	The ratio of provisions for loan losses to total loans. The higher this ratio is, the poorer the quality of loan portfolio.
	Loan loss provisions/equity (LLPE)	Negative	The ratio of provisions for loan losses to total equity.
	Loan loss reserve/Gross loans (LLRGL)	Negative	The ratio of loan loss reserve to gross loans (loans plus loan loss reserves) indicates how much of the total loan portfolio is provided for but not charged off. Given a similar charge-off policy, the higher the ratio, the poorer the quality of the loan portfolio.
	Loan loss reserve/Total equity (LLRE)	Negative	The ratio of reserve for loan losses to total equity.
Liquidity	Interbank ratio (IBR)	Positive	This is money lent to other banks (due from other banks) divided by money borrowed from other banks (due to other banks). If this ratio is greater than 1, then it indicates the bank is a net placer rather than a borrower of funds in the market place and therefore more liquid.
	Net loans/Total assets (LR)	Negative	This liquidity ratio indicates what percentage of bank assets is tied up in loans. The higher this ratio, the less liquid the bank is and hence the lower the bank FSR issued. LR is also known as loan ratio.
	Net loans/Deposit and short-term funding (NLDSTF)	Negative	This ratio is another measure of bank liquidity. Apparently, a high figure denotes lower liquidity.
	Net loans/Total deposit and borrowing (NLTDB)	Negative	This ratio is similar to NLDSTF except that NLTDB's denominator only includes deposits and borrowings with the exception of capital instruments (i.e., total deposits and borrowings = customer and short-term funding plus other funding minus hybrid capital and subordinated debt).
	Liquid assets[40]/Deposit and short-term funding (LADSTF)	Positive	This is a deposit run-off ratio. It focuses mainly on the percentage of customers and short-term funds that must be met if they are withdrawn suddenly. The higher this percentage, the more liquid is the bank and the less vulnerable to a run

[40] Liquid assets are short-term assets that can be easily converted into cash, such as cash itself and deposits with the central bank, treasury bills, other government securities and interbank deposits.

		on the bank.
Liquid assets/Total deposit and borrowing (LATDB)	Positive	This ratio is similar to LADSTF but LATDB shows the amount of liquid assets as a proportion of total deposits and borrowing

Source: Developed by the researcher

3.2.4 Control variables

The methodology examines other factors that may have an effect on bank FSR. Bank financial performance variables are controlled for the following four variables:

(1) Country as a dummy variable to control for country variations;

(2) The size effect as a dummy variable (Ln Assets). Size is classified into three size levels: large, medium and small[41];

(3) Time effect as a dummy variable to control for the effect of time; and

(4) CI's national long-term credit rating (i.e., country sovereign ratings [SR]) reflects country-specific effects that result from differences in regulation and supervision rules implemented by each country. SR indicates the probability of government default on its obligation (Laere et al., 2012). Consequently, SR captures important macroeconomic and institutional characteristics of countries in which banks are located (Poon et al., 2009). The following factors are expressed in SR: exchange rates, inflation, regulatory environment, taxation, infrastructure availability, labor market condition and the size, structure, and growth of the economy.

It is noteworthy that SR is issued based on certain economic and political risks such as fiscal policy and budgetary flexibility, income and economic structure, stability of political institutions, monetary policy and inflation pressures and public and private sector debt burdens. The SR scale comprises 20 categories

[41]Size reflects qualitative factors, such as geographic and product diversification.

(from nrAAA to nrD). The categorical ratings are converted into a numerical scale, with the largest numerical value (20) assigned to the countries with highest ratings (nrAAA). This numerical conversion was used by Hammer et al. (2012) and Ferri et al. (1999).

Some research has highlighted the importance of country-specific effects as a determinant of bank rating. For example, Caporale et al. (2011), using financial variables of EU countries' bank ratings, found that country-specific indicators are vital determinants of bank rating. The researchers found that banks located in so-called new EU countries have lower bank ratings than banks located in old EU countries because of country-specific effects. Belloti et al. (2011b) presented similar evidence by applying ordered choice estimation techniques and a support vector machine to identify the impact of financial variables and country risk on the prediction of FBRs. The authors found that the inclusion of the country effect enhanced the predictive performance of both econometric predictive techniques. In addition, banks located in more stable, developed and rich countries tend to obtain high ratings.

Similarly, Shen et al. (2012), using S&P's long-term credit rating for rated banks in 86 countries, found that banks located in countries with high sovereign credit ratings tend to receive high bank credit ratings. Godlewski (2006), using a sample of emerging market economies, found that good institutional environment quality positively affects the national reputation and thus enhances the reputation of banks. Thus, the inclusion of SR is expected to improve the explanatory power as well as the predictive capabilities of the models tested in this thesis.

3.3 Statistical estimation models

This section provides a discussion of different models, statistical techniques and three evaluation criteria used in this thesis to evaluate the predictive capabilities of the proposed predictive techniques.

3.3.1 Multicollinearity

Multicollinearity implies that two or more variables are very closely linearly related, which makes it difficult to determine reliable estimates of their individual regression coefficients (Field, 2010). In other words, two independent variables convey the same information. In addition, multicollinearity has negative impact on model results. This is mainly because it is difficult to separate the influential relationship between supposedly independent variables. That is, correlated variables contribute redundant information to the regression model. This leads to unstable coefficients that result in coefficient signs that do not match expectations.

This thesis addresses the issue of multicollinearity by examining the variance inflation factor (VIF) scores. The regression analysis is conducted a number of times to trace the variables associated with VIF scores > 5. The VIF is estimated as follows (Studenmund, 2000, p. 257):

$$\mathrm{VIF}\left(\hat{\beta}_i\right) = \frac{1}{\left(1 - R_i^2\right)} \tag{1}$$

The decision rule states that if the VIF coefficient for any independent variable is equal to one, this implies that collinearity has no significant effect on the relationship between independent variables. However, when variables associated with the VIF coefficient are greater than five, the independent variable is excluded from the regression equation. The decision to drop a variable has a goal of reducing multicollinearity as much as possible, thus improving the significance of other variables that are not substantially correlated with each other (Berenson et al., 2005). In addition, a pair-wise correlation matrix among independent variables is estimated to test whether independent variables are correlated and thus validate VIF results.

3.3.2 Multinomial logit (ML) model

The nature of the dependent variable mainly necessitates the use of ML technique, which is a generalisation of the logistic regression. This is mainly because the dependent variable (i.e., bank FSRs) is polytomous, that is, its values are more than two categories (Sentas and Angelis, 2006). A similar related technique (i.e., an ordered logistic regression ‘logit’) has been used in a number of empirical studies (Eisenbeis, 1978; Poon et al., 1999; Pasiouras et al., 2006; Pasiouras et al., 2007; Öğüt et al., 2012; Hammer et al., 2012). In this case, the data are called individual specific.

The problem of the ordered methods is that variables may influence credit ratings differently across different rating categories. The multinomial or unordered logit model allows the importance of variables to vary across ratings (Matthies, 2013). In addition, the ordered models assume a constant influence of variables across all rating categories. Ederington (1985) states that unordered logit achieves the best fit for in-sample estimation and ordered logit performs best for out-of sample prediction.

Altman and Rijken (2006) state that the ordered probit panel regression assumes a point-in-time perspective instead of the through-the-cycle approach that is employed by rating agencies. This is problematic if the probit method is used to forecast rating changes (Amato and Furfine, 2004). Distinguin et al. (2013) find that the operational aspects of multinomial logistic allow for possible asymmetric effects, therefore, they use it for predicting bank ratings.

The estimation description of ML model is as follows (Greene, 2000, p. 859):

$$\text{Prob}(Y = j) = \frac{e^{\beta_j' \mathbf{x}_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' \mathbf{x}_i}} \text{ for } j = 1,2,..., J \tag{2}$$

Where

Y represents the dependent variable, i.e., bank FSRs, which takes integer values from 1 to J. j denotes the number of bank FSRs rating categories ranging from 1 (D) to 20 (AAA), e is the base of natural logarithm (2.71828), β_j represents the regression coefficient corresponding to outcome j, $\mathbf{x}_i$ are explanatory variables describing observation i (i.e., financial and nonfinancial variables). The estimated equations provide a set of probabilities for the J+1 choices for a decision maker with characteristics $\mathbf{x}_i$. The estimation of the ML model is straightforward. Newton's method provides a ready solution. The log-likelihood can be derived by defining, for each individual (or each bank FSR), $d_{ij} = 1$ if alternative j is chosen by individual i, and 0 if not, for the J-1 possible outcomes. Then for each observations i, one and only one of the d_{ij} 's is 1. It is worth noting that if the data are in the form of ratios, then the appropriate log-likelihood and derivatives are obtained just by making $d_{ij} = n_i p_{ij}$

The log likelihood is a generalisation of that for the binomial or logit model:

$$\ln L = \sum_{i=1}^{n} \sum_{j=0}^{J} d_{ij} \ln \Pr ob(Y_i = j) \tag{3}$$

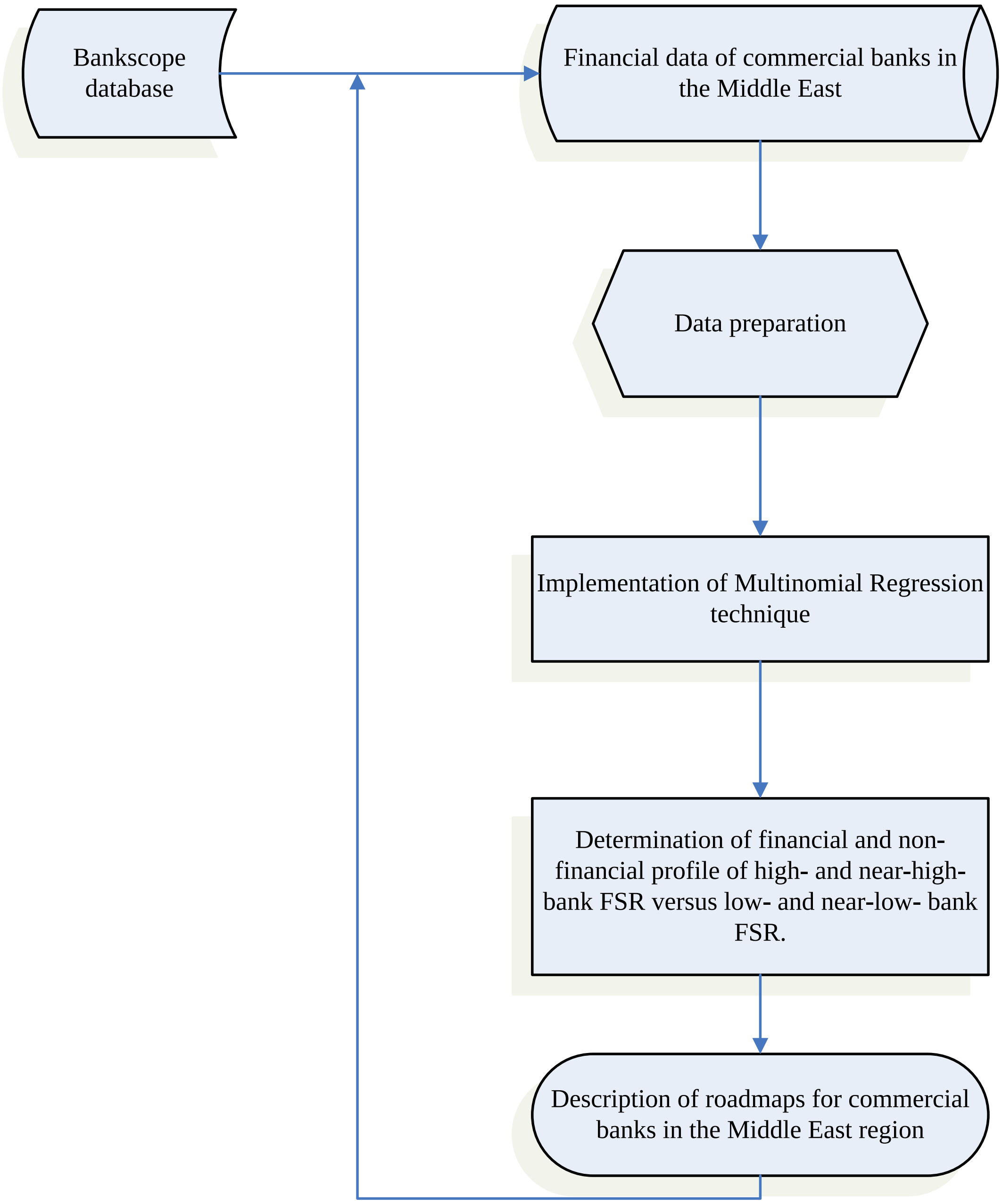
The derivatives have the characteristically simple form:

$$\frac{\partial \ln L}{\partial \boldsymbol{\beta}_j} = \sum_i \left[d_{ij} - P_{ij}\right]\mathbf{x}_i \quad \text{for } j = 1, ..., J$$

Where

d_{ij} represents the log likelihood (the probability of occurrence for each bank FSR). The independent variables are bank equity ratio (proxy for bank CS) in addition to the financial variables of bank performance that include asset quality, capital adequacy, credit risk, liquidity and profitability. Non-financial variables are also included to assess country, bank size, time and country sovereign ratings impact on bank FSR simultaneously with bank CS and financial variables. These are used as the factors in the estimation procedures. Figure 3-1 illustrates the ML model.

Figure 3.1: Flow chart diagram of the ML model



3.3.3 The process of choosing statistical predictive techniques

One of the main thrusts of the current thesis is to predict banks' FSR group memberships and choose the most accurate predictive statistical techniques to enhance the predictive capability of banks' FSR group memberships for commercial banks located in the Middle East region.

Using PASW® Modeler 14[42], the researcher applied the auto classifier node as an initial step to create automatically and compare a number of statistical predictive techniques.

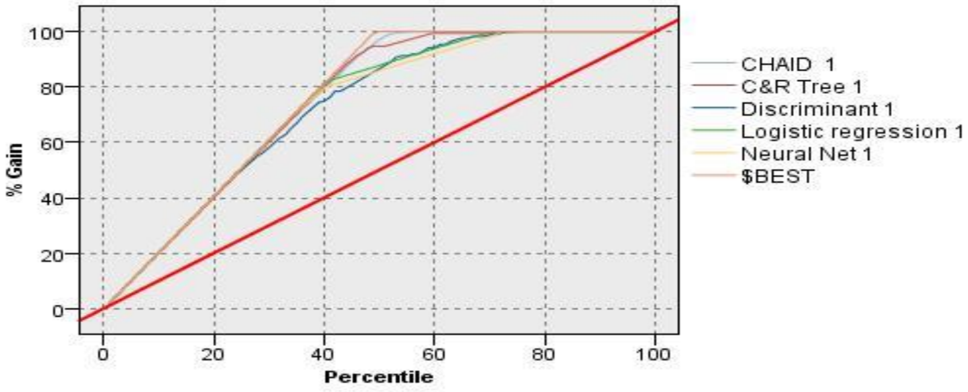
In a relatively simple stream, auto classifier node generates and ranks a set of candidate predictive statistical techniques and chooses the ones that perform the best. The auto classifier node specifies the number of statistical models to be created, along with the criteria used to compare statistical techniques. This thesis used the overall accuracy percentage to rank the predictive statistical techniques. The overall accuracy percentage identifies the percentage of observations that are correctly predicted by the statistical technique relative to the total number of observations (SPSS, Inc., 2010).

Accordingly, the auto classifier ranks at the top two decision-tree techniques: CHAID with 96.30% overall accuracy and CART with 95.44% overall accuracy. This is followed by MLP neural networks with 94.02% overall accuracy. The two conventional multivariate statistical techniques (i.e., DA, with 93.16% overall accuracy, and LR, with 73.5%) are ranked as the lowest predictive statistical techniques. Thus, it can be concluded that the machine-learning techniques (i.e., CHAID, CART and MLP neural networks) are superior to the conventional techniques (i.e., DA and LR) for predicting bank FSR group membership in the specific environment chosen (i.e., the Middle East region).

Moreover, the auto classifier node generates an evaluation chart that offers a visual way to assess and compare the performance of each predictive statistical technique. As shown in Figure 3.2, the five predictive statistical techniques are plotted to highlight the differences between each of them in terms of overall accuracy percentage.

[42] PASW® Modeler 14 is the SPSS enterprise-strength data mining workbench that helps the author building predictive models quickly and intuitively without programming

Figure 3.2: An evaluation chart for the five predictive statistical techniques



3.3.3.1 Evaluation criteria

The present study used three evaluation criteria: average correct classification (ACC) rate criterion, estimated misclassification cost (EMC) criterion and gains charts. The ACC rate criterion is significant in evaluating the classification capability of the proposed statistical predictive techniques. The EMC criterion is used to evaluate the overall statistical technique effectiveness and to find the minimum EMC for the proposed statistical predictive techniques. Finally, gains charts are a useful way to visualise the quality of the predictive model.

3.3.3.1.1 Average correct classification criterion

As shown in Table 3.4, the initiative of ACC rate evolved from a matrix titled ‘A Confusion Matrix’, ‘Classification Matrix’ or ‘Accuracy Matrix’ (Abdou, 2009b; Altman, 1968; Yang et al., 2004).

Table 3.4: Classification matrix

	Predicted observations		
Actual observations	h	l	
H	H_h	H_l	TH
L	L_h	L_l	TL
	Th	Tl	TN

Note. H = actual high FSR; h = predicted high FSR; L= actual low FSR; l = predicted low FSR; H_h = actual high FSR/predicted high FSR ; H_l = actual high FSR/predicted low FSR; L_h = actual low FSR/predicted high FSR; L_l = actual low FSR/predicted low FSR; TH = total actual high-FSR observations; TL = total actual low-FSR observations; Th = total predicted high-FSR observations; Tl = total predicted low-FSR observations; and TN = total number of observations in the dataset.

Table 3.4 shows that a number of useful rates can be calculated from this matrix. The first rate is the ACC rate, given by (Hh + Ll)/TN. The second rate is a complementary value of the ACC rate; that is, total error rate represented by (Hl + Lh)/TN. The third rate is subdivided into two sub-rates known as the correctly classified high-FSR rate (Hh/TH) and the correctly classified low-FSR rate (Ll/TL). Finally, the fourth rate also is subdivided into two sub-rates called Type I error rate (Hl/TH) and Type II error rate (Lh /TL).

In this thesis, the ACC rate is considered to be an important criterion to be used, especially for banks in the Middle East, because it highlights the accuracy of prediction. In addition, the ACC rate ignores various misclassification costs for actual low FSR/predicted high FSR and the actual high FSR/predicted low FSR. The ACC rate measures the proportion of the correctly classified cases (high FSR and low FSR) in the Middle East bank dataset.

3.3.3.1.2 Estimated misclassification cost criterion

The second evaluation criterion is the EMC criterion, which is computed by the equation that follows (Abdou, 2009b; West, 2000):

$$EMC = C(I) \times (H_l/TH) \times (TH/TN) + C(II) \times (L_h/TL) \times (TL/TN) \quad (4)$$

where C(I) is the misclassification cost associated with a Type I error; (Hl/TH) is the probability of a Type I error expressed as a ratio of number of high FSRs predicted as low FSRs (Hl) to total high FSRs (TH); (TH/TN) is the prior probability of high FSRs, specifically, the ratio of total high FSRs (TH) to the total number of observations (TN); C(II) is the misclassification cost associated with a type II error; (Lh/TL) is the probability of Type II error, expressed as a ratio of low FSRs predicted as high FSRs (Lh) to total low FSRs (TL); and (TL/TN) is the prior probability of a low FSR, that is, the ratio of total low FSRs (TL) to the total number of observations (TN).

It is worth mentioning that there is a significant difference between the costs associated with Type I and Type II errors. Generally, the misclassification cost associated with Type II error is much higher than that associated with Type I error (Abdou 2009b; Lee and Chen, 2005). Hans Hofmann, who contributed the German credit-scoring data, recommended that the ratio of misclassification costs associated with Type I and Type II errors be set to 1:5 (West, 2000). In this thesis, the importance is not only on this relative cost ratio at 1:5, but also that it provides a sensitivity analysis using higher cost ratio at 1:12. This is mainly because it is expected that the higher cost ratio might be more appropriate, especially for an environment with high political risk such as countries in the Middle East region.

3.3.3.1.3 Gains chart

The gains chart plots the values in the gain (%) column from the gains table. Gains are defined as the proportion of hits in each increment relative to the total number of hits in the tree using equation (5):

$$\text{(hits in increment / total number of hits) x 100\%} \qquad (5)$$

The diagonal line plots the expected response in the testing subsamples if the models are not used. The curved line indicates how much the model can be improved by including only those that rank in the higher percentiles based on gain. The steeper the curve, the higher the gain (SPSS, Inc., 2010).

3.3.4 CHAID

CHAID is a data analysis method used to examine the association between a dependent variable and a large series of independent variables (Koyuncugil and Ozgulbas, 2012). CHAID is used to predict and detect interactions between variables (Bijak and Thomas, 2012). The CHAID method is a statistical technique for segmentation and is considered a tree-structured classification method (Kass, 1980). The CHAID algorithm is an enhancement of the automatic interaction detection method designed for a categorised dependent variable (Magidson and Vermunt, 2005). The main objective of CHAID is to split the data into mutually exclusive and exhaustive subsets that best describe the dependent variable (Kass, 1980).

CHAID examines all values of a potential independent variable using the significance of a statistical test as a criterion. Using stepwise procedures, values that are statistically homogeneous are merged with respect to the dependent variable and all other values that are heterogeneous are maintained. Subsequently, the first branch in the decision tree is developed by selecting the best independent variable. This iterative process concludes with child node that groups all homogenous values of the selected independent variable. This process is repeated until the tree is fully grown and no more nodes can be split.

The measurement level of the dependent variable determines the statistical test. That is, the F test is used for a continuous dependent variable and the chi-squared test is used for a categorical dependent variable to determine the best next split at each step (SPSS, Inc., 2010).

In this thesis, the Pearson chi-squared test is used because it fits the nature of data. The chi-squared statistics are calculated using the observed cell frequencies and the expected cell frequencies, and the *p*-value is based on the calculated statistics.

The Pearson chi-squared statistic is calculated as per SPSS, Inc. (2010, p. 77):

$$X^2 = \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{(n_{ij} - \hat{m}_{ij})^2}{\hat{m}_{ij}} \tag{6}$$

where $n_{ij} = \sum_n f_n I(x_n = i \wedge y_n = j)$ is the observed cell frequency and $\hat{m}_{ij}$ is the expected cell frequency for cell $(x_n = i, y_n = j)$ from the independence model. The corresponding *p*-value is calculated as $p = \Pr(x_d^2 > X^2)$, where x_d^2 follows a chi-square distribution with d = (J – 1)(I – 1) degrees of freedom.

The Bonferroni correction method[43] is used to adjust the test significance level for numerous tests completed at the same time (Dunn, 1961; Hawkins and Kass, 1982). The adjusted *p*-value is computed by multiplying the *p*-value by a Bonferroni multiplier. The Bonferroni multiplier manages the overall *p*-value across multiple statistical tests. Suppose that an independent variable originally has I categories and after the merging step, this number is reduced to r categories. The Bonferroni multiplier B is the number of possible ways that I categories can be merged into r categories. For r = I, B = 1, for 2 ≤ r < I (SPSS, Inc., 2010,p.79).

$$B = \sum_{v=0}^{r-1} (-1)^v \frac{(r-v)^I}{v!(r-v)!} \tag{7}$$

The CHAID method has certain advantages as a means of identifying logical patterns in complicated datasets. First, the CHAID method produces more than two categories at any particular level in the tree as it is not a binary tree method. This iterated process produces a

[43] It is named after Italian mathematician Carlo Emilio Bonferroni for the use of Bonferroni inequality.

wider tree than that provided by binary growing methods. Second, the CHAID method can work for all levels of measurements for the dependent variable and independent variables (e.g., nominal, ordinal or interval). Finally, the missing values in the independent variables are treated as a floating category so that partial data can be used whenever possible within the tree[44].

In the literature of finance, the CHAID algorithm has been used for development of early warning system models for financial risk detection in several research studies (Koyuncugil and Ozgulbas, 2007, 2012). In addition, the CHAID algorithm has been used to develop credit scoring models by which to assess the credit risk of bank customers (Bijak and Thomas, 2012; Thomas et al., 2002; Yap et al., 2011). To the best of this researcher's knowledge, this is the first research that has used the CHAID algorithm to predict banks' FSR group memberships for commercial banks in the Middle East region.

3.3.5 CART

The CART method is a nonparametric statistical procedure and a binary decision tree-based algorithm popularised by Breiman et al. (1984). As the name suggests, the CART algorithm is a single procedure that can be used to solve both regression and classification problems using a set of *if-then* rules (Razi and Athappilly, 2005). CART is a classification tool used to classify an object (i.e., data groups and/or firms) into two or more populations. CART is a very flexible, reliable, transparent and comprehensible decision-tree tool that automatically separates complex databases to isolate significant patterns and relationships (Chandra et al., 2009; Ravi et al., 2008).

[44] The floating category mean that independent variable with missing data will be either separated out on its own or grouped with categories near one end of the ordinal part of the scale.

The CART method outlined in Breiman et al. (1984) is divided into three stages: (1) construction of the maximum tree (tree-growing process), (2) selection of the right-sized tree (pruning process), and (3) classification of the new data using the constructed tree.

The first stage involves the tree-growing process in which CART uses a recursive partitioning technique to partition data into two homogeneous subsets. Those two subsets are then split again using a splitting criterion that generates the greatest improvement in predictive accuracy. Depending on the type of dependent variable, several criteria are available to reduce the impurity in splitting for classification. Gini or towing is used with a categorical dependent variable and least-squared deviations are used with a continuous dependent variable (SPSS, Inc., 2010). In this thesis, the Gini index is used because it fits the nature of the data and is the most broadly used rule. The splitting process is repeated until the homogeneity criterion is attained or until some other stopping criterion is fulfilled.

The Gini index uses the following impurity function g(t) at a node t in CART tree as follows (SPSS, Inc., 2010, p.63):

$$g(t) = \sum_{j \neq i} p(j \mid t)p(i \mid t) \tag{8}$$

where i and j are categories of the dependent variable, and

$$p(j \mid t) = \frac{p\ (j,t)}{p(t)}$$

$$p(j \mid t) = \frac{\pi(j)N_j\,(t)}{N_j}$$

$$p(t) = \sum_{j} p(j,t)$$

where $\pi(j)$ is the prior probability value for category j, $N_j\,(t)$ is the number of records in category j of node t, and N_j is the number of records of category j in the root node. It should be noted that Gini index is used to enhance splitting during tree growth, thus only those records in node t and the root node with valid values for the split predictor are used to compute $N_j(t)$ and N_j, respectively.

After a fully grown tree is identified, the second stage, called the *pruning process*, is implemented to improve the generalisation and to avoid over-fitting. The pruning process investigates the entire decision tree and then eliminates the bottom-level splits that do not add significantly to the accuracy of the tree. The main objective of the pruning process is to generate a right-sized tree in which the misclassification risk is smaller than that of the largest possible tree. This is achieved by employing two pruning algorithms: optimisation by number of points in each node and cross-validation.

The former algorithm implies that the splitting is stopped when the number of observations in the node is less than predefined required minimum. The latter algorithm is based on an optimal proportion between the misclassification error and the complexity of the tree. Thus, the cross-validation process focuses on minimising both the misclassification risk and the complexity of the tree to obtain the optimal tree. This task is accomplished using the minimal cost-complexity function (SPSS, Inc., 2010, p.67):

$$R_\alpha(T) = R(T) + \alpha\left|\tilde{T}\right| \tag{9}$$

$R(T)$ is the misclassification risk of tree T, and $\left|\tilde{T}\right|$ is the number of terminal nodes for tree T. The term α represents the complexity cost per terminal node for the tree.

The third stage is to classify the new data after the construction of a right-sized tree with the lowest cross-validated rate. The outcome of this stage is that each new observation is assigned to a class or response value. Each new observation will fit with one of the terminal nodes of the tree through a set of questions in the tree.

The main advantage of the CART method can be summarised as follows. First, the CART algorithm is a nonparametric technique and thus does not require specification of any functional form. Accordingly, CART is not affected by the outliers. This feature is important especially for financial data in which outliers exist as a result of financial crises or defaults. Also, CART considers unequal misclassification costs in the tree-growing process and specifies the prior probability distribution in a classification problem. Finally, the CART algorithm handles noisy and incomplete data and provides easy-to-use decision trees that reveal variable interactions in the data set.

In the literature of finance, the CART algorithm has been applied to solve problems such as firm bankruptcy prediction (Brezigar-Masten and Masten, 2012; Chandra et al., 2009; Chen, 2011; Li et al., 2010). In the field of banking, the CART algorithm has been used to develop credit scoring models by which to assess the credit risk of bank customers (Chen et al., 2009; Kao et al., 2012; Lee et al., 2006). In addition, the CART algorithm has been used to develop early warning models by which to assess the soundness of individual banks (Loannidis et al., 2010) and to predict bank performance (Ravi et al., 2008). To the best of the researcher’s knowledge, this is the first study to use the CART algorithm to predict banks’ FSR group memberships for commercial banks in the Middle East region.

3.3.6 Neural networks

Neural networks are an information processing technology that mimics the processing characteristics of the human brain. The study of neural networks was first proposed by McCulloch and Pitts (1943), who explained the threshold neuron as a model that simulates the working principle of the human brain. This mean that the learning ability of human beings is transferred to a computer environment in which neural networks are able to learn from examples (Akkoc, 2012).

Neural networks are nonparametric models and computational tools employed to examine data and develop models to identify significant patterns or structures in the data, which is known as *training data*. Once the neural network is familiar with the training data and learns its patterns, the neural network is employed for new data (i.e., testing data) and thus achieves a variety of outcomes. The neural network possesses certain strengths not found in other statistical techniques, such as no prior assumption is required, tolerance of noisy or random inputs, self-organisation and learning, generalisation from specific examples and discovery of complex relationships among inputs (Udo, 1992, 1993). These abilities create a machine that possesses a reasoning process similar to that of the human brain.

Widrow et al. (1994) argued that most neural network applications fall into three main categories: (1) pattern classification, (2) prediction and financial analysis and (3) control and optimisation. Because of the overlap between pattern classification and predictive application, Widrow et al. introduced a modified categorisation that separates application by methods. This resulted in three categories: (1) classification, (2) time series and (3) optimisation.

The classification problems entail either binary decisions or multiple-class identification in which observations are divided into categories based on specified characteristics. In time-series problems, neural networks develop a forecasting model using the historical data set to predict future data points. Finally, the optimisation problems require application of neural networks to solve very difficult problems known as non-polynomial complete problems (e.g., job-scheduling in manufacturing). In sum, neural networks can be employed to: (1) learn to predict future events depending on pattern observed in the historical training data, (2) learn to classify unobserved data into determined groups according to characteristics defined earlier in the training data, and (3) learn to cluster the training data into natural groups according to comparable characteristics in the training data (Smith and Gupta, 2002).

Neural networks are used successfully across a wide range of problem domains, in areas such as finance, medicine, engineering, geology and physics. In the field of finance, neural networks are employed to deal with uncertainty by recognising data patterns and using these patterns to predict future events. Medsker et al. (1993) stated that neural networks are used in different financial analysis tasks such as credit authorisation screening, mortgage risk assessment and financial and economic forecasting. Moreover, neural networks have been adapted to improve significantly the potential of corporate finance applications such as financial simulation, prediction of investor behaviour, investment evaluation, credit approval, pricing of initial public offerings and determination of optimal capital structure (Hsieh, 1993).

In addition, neural networks have been successfully trained to predict bank failure (Boyacioglu et al., 2009; Chauhan et al., 2009; Kumar and Ravi, 2007; Loannidis et al. 2010; Markham and Ragsdale, 1995; Ravi and Pramodh, 2008; Salchenberger et al., 1992; Tam, 1991; Tam and Kiang, 1990, 1992; Zhao et al., 2009;) as well as firm bankruptcy (Brockett et al,. 1994; Chandra et al., 2009; Chen et al., 1995; Falavigna, 2012; Fletcher and Goss, 1993; Hsiao and Whang, 2009; Kim and Kang, 2010; Lee et al., 2005; Tsukuda and Baba, 1994; Udo, 1993; Wilson and Sharda, 1994; Zhang et al., 1999). In line with this, Huang et al. (2004) employed a back-propagation neural network to evaluate the creditworthiness of US and Taiwanese banks, and Öğüt et al. (2012) employed neural networks to predict BFSRs issued by Moody’s for Turkish banks during the period from 2003 to 2009.

3.3.6.1 Neural network fundamentals

Neural networks were inspired by the biological sciences as they represent an extremely simplified model of the brain. Neurons are the cells found in the human brain and nervous system. Each neuron is a specialised cell that can propagate an electrochemical signal. These signals or information are carried to a neuron through a branching input structure called *dendrites*. On the other hand, electrochemical signals are transmitted from neurons via a branching output structure known as *axons*. Synapses are the gaps or junctions between the connections used by neurons to communicate with each other (Picton, 2000).

Neurons fire electrochemical signals along the axon. This signal is transferred via synapses to the dendrites of other neurons. According to the incoming electrochemical signals, synapses release the neurotransmitters that excite or inhibit their associated neuron activity. Thus, a neuron retains all of the activating signals and disregards all of the inhibiting signals from all of its synapses. Neurons fire to their axon only if the difference is higher than its threshold of activation. Consequently, a neuron may send/receive an electrochemical signal to/from other neurons. This means that neural networks are composed of a number of processing elements, each of which has a number of inputs that combine to produce a single output (Abdou et al., 2008).

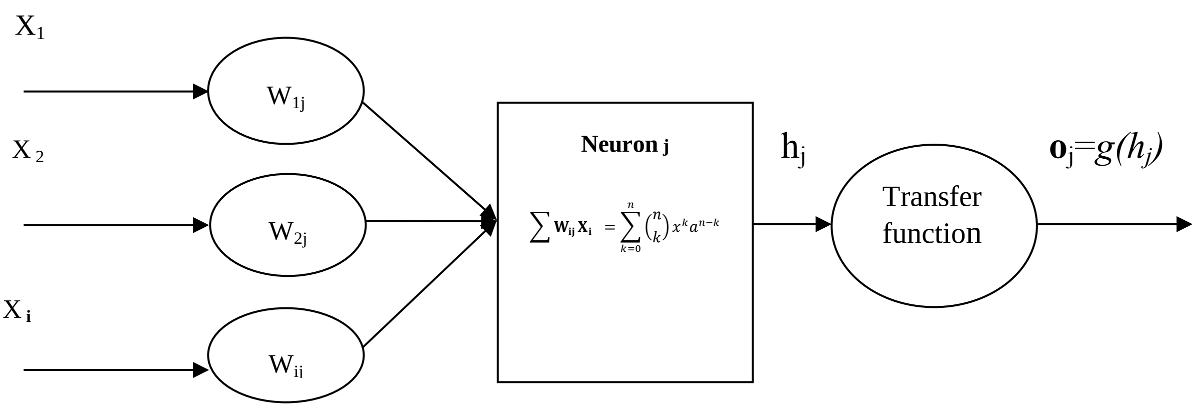
3.3.6.2 The structure of neural networks

The basic element of a neural network is artificial neurons that are linked together to form either a single layer or multiple layers. The type of neural network determines the basic neuron elements employed. A neuron is a simple virtual device that receives a number of inputs either as raw data inputs or outputs from the preceding neuron. Each neuron sums all inputs and performs a (usually nonlinear) transfer function to generate an output. The output value is either a final model prediction or is used as one of the inputs to other neurons (SPSS, Inc., 2010).

The structure of a neural network is composed of many neurons connected in a systematic way. The most common neural network structure consists of three basic layers: (1) an input layer that represents a layer for input neurons where external information (independent variables in statistics) is received; (2) one or more hidden layers that perform the internal processing on information received from input layer and (3) the output layer, which represents a layer for output neurons where information is transmitted outside of the neural network (dependent variable in statistics).

These layers are fully interconnected with each other. That is, each neuron in the input layer is connected to every neuron in the hidden layer and each neuron in the hidden layer is connected to every neuron in output layer. Each connection has its associated weight, which verifies the power of one neuron over another. Each weight may have either a positive or a negative value attached to it. Positive weights indicate reinforcement and negative weights are associated with inhibition (Irwin et al., 1995). As shown in Figure 3.3, predictions are generated by the information flow from the input layer via the processing layer (i.e., hidden layer) to the output layer.

Figure 3.3: Basic neuron model



Source: Based onIrwin et al. (1995), p. 3; Brockett et al. (1994); and Udo (1993), modified by the author

Figure 3.3 shows a neural network structure with inputs ($X_1, X_2, \ldots. X_i$) connected to neuron j with weights ($W_{1j}, W_{2j} \ldots.. W_{ij}$) on each connection. After multiplying each input signal by its associated weight, the neuron adds all of the received input signals. This results in an output (h_j) that passes through a transfer (activation) function, $g(h_j)$, which is normally non-linear, to conclude with the final output O_j.

3.3.6.3 Multilayer perceptron

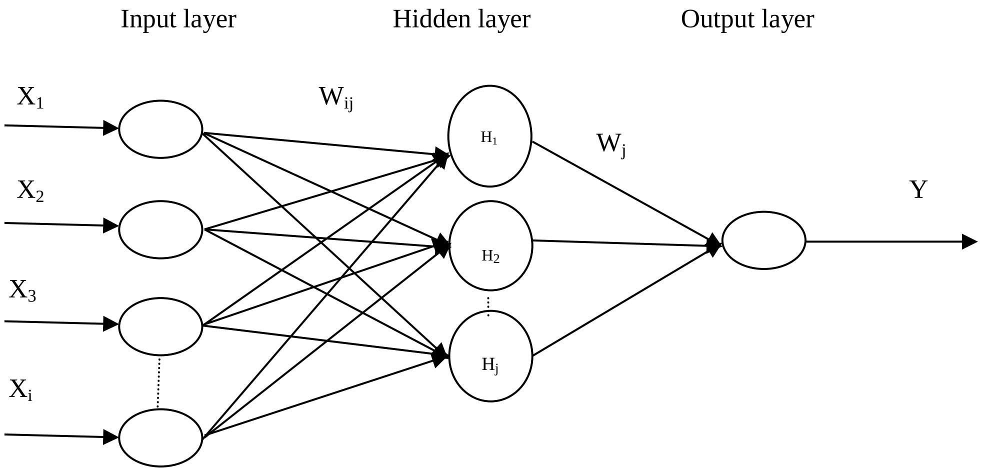
PASW® Modeler 14 offers two different types of neural networks: MLP and radial basis function. In this thesis, MLP is employed because of the categorical nature of the dependent variable. MLP is one of the most frequently used neural network models. It is applied in approximately 95% of the reported neural network business application studies, mainly for prediction, classification and modelling (Wong et al., 1997). MLP is utilised to solve problems that concern learning the relationships between a set of inputs and a known output.

MLP is a feed-forward neural network with up to two hidden layers. MLP is a supervised learning network that permits weights to be learned from experience, based on empirical observations of the object of interest (Rumelhart et al., 1986; Salchenberger et al., 1992). That is, any non-linear function can be approximated by adjusting or training the supervised network based on the given input-output pairs. An MLP network is a function of one or more independent variables that minimises the prediction error of the dependent variable. The training of an MLP involves the minimisation of an error function based on the generalised delta rule using a back-propagation algorithm (SPSS, Inc., 2010). Back propagation is the most popular example of a neural network training algorithm used to calculate the gradient of the network; that is, to calculate the first derivatives of the error function with respect to each network weight (Fausett, 1994; Lee et al., 2005; Patterson, 1996).

The calculation of neural network weights is known as the *training process*. In the training process, the input data feed forward via the network to generate a prediction from the output layer. The network compares the predicted output to the actual output and calculates the error. In an attempt to improve the overall predictive accuracy, the difference between the actual output and the predicted output is propagated backward (i.e., as an error function) via the network to adjust and update the connection weights. This process is repeated until either the error function is sufficiently close to zero or the default number of iterations is reached.

Figure 3.4 shows an example of MLP feed-forward architecture. The architecture consists of three main layers: (1) the input layer, which consists of neurons of all input variables (X_i); (2) the last layer, which is the output layer, which is one neuron (Y) and (3) the interior layer(s), called the middle or hidden layer(s), which have three neurons in this architecture (H_j).The flow of data is from left to right, with input (X_i) passed via the network through connecting weights to the hidden layers of neurons and subsequently to the output layer.

Figure 3.4: MLP feed-forward architecture (one hidden layer)



Source: Modified by the author from Erbas and Stefanou (2009), Fletcher and Goss (1993),Lee et al. (2005), Limsombunchai et al. (2005), Sermpinis et al. (2012), Smith and Gupta (2000) and Udo (1993) .

Accordingly, the following equation explains the MLP feed-forward function for one hidden layer:

$$Y= F\ \left[\sum_{j=1}^{J} W_j . F_j \left(\sum_{i=1}^{i} W_{ij}\, X_i\right)\right] \tag{10}$$

where Y = the output of the network, F = the logistic (sigmoid) transfer function, $(X) = \frac{1}{1+e^{-X}}$, for the output layer, W_j = the connection weights from hidden layer (node j) to output layer, F_j= the logistic transfer function for the hidden layer, W_{ij} = the connection weights from input layer (node i) to hidden layer (node j) and X_i = the input variable for node i (Brown and Mues, 2012; Erbas and Stefanou, 2009; Limsombunchai et al., 2005; Salchenberger et al., 1992).

3.3.7 Discriminant function

It is sometimes useful to determine functions of the variables $X_1, X_2, \ldots, X_p$ that in some sense separate the *m* groups. The simplest approach involves the use of a linear combination of the X variables for this purpose in such a way that Z reflects group differences as much as possible (Eldomiaty et al., 2011):

$$Z = a_1 X_1 + a_2 X_2 + \ldots + a_p X_p \tag{11}$$

Groups can be well separated using Z if the mean value changes considerably from group to group, with the values within a group being fairly constant. One way to choose the discriminant coefficients $a_1, a_2, \ldots, a_p$ in the index is to maximise the *F* ratio for a one-way analysis of variance. Hence a suitable function for separating the groups can be defined as the linear combination for which the *F* ratio is as large as possible.

When this approach is used, it turns out that it may be possible to determine several linear combinations by which to separate groups. In general, the number available is the smaller of p and *m*-1. This is one of the advantages of the linear DA. That is, the reduction of the analysis space dimensionality (i.e., from the number of different independent variables X to *m*-1 dimension[s]). In this stage, the researcher is concerned only with two groups: banks with high FSRs versus those with low FSRs, so the resulting Z function is only one function (i.e., one-dimension analysis).

When discriminant coefficients are applied to the actual ratio, a basis exists for classification into one of the mutually exclusive groups. In this regard, the DA technique has the advantage of considering an entire profile of characteristics common to the relevant observations (i.e., banks with high FSRs) as well as the interaction of these characteristics. The linear DA also has the advantage that it yields a model with a relatively small number of selected measurements, which has the potential to convey a great deal of information (Altman, 1968; Altman and Sametz, 1977).

3.3.7.1 Discriminant analysis (Z-score model)

The DA was initially introduced by Fisher (1936) as a classification technique. The DA is the most common technique used to develop Z-score models. The DA addresses the problem of the quality of separation into two or more groups of observations (i.e., individuals, companies, banks), given measurements for these observations on several variables (Hair et al., 2005; Manly, 2004). Therefore, the DA is a statistical technique used to identify and weigh the significant measures that accurately classify original observations into their identified groups. The DA is used primarily to classify and/or make predictions in problems in which the dependent variable appears in qualitative form (e.g., high- or low-risk stocks, bankrupt or non-bankrupt, high versus low FSRs). Accordingly, the qualitative form is to be classified into two different groups.

In the field of business,Altman (1968), Altman and Sametz (1977) and Altman and Fleur (1984) initiated the DA by building a z-score model that uses public accounting information to discriminate between bankrupt and non-bankrupt firms. There are many Z models in the DA, most of which were derived for the evaluation of company solvency and the assessment of financial distress across different industries and in different countries.

In the literature of finance (Altman, 1973; Blum, 1974; Boyacioglu et al., 2009; Canbas et al., 2005; Deakin, 1972; Doğanay et al., 2006; Edmister, 1972; Li et al., 2010; Pettway and Sinkey, 1980; Santomero and Vinso, 1977; Sinkey, 1975; Taffler, 1978, 1982, 1983, 1984; Wilcox, 1971) applies many forms of DA to predict corporate and bank failure and to assess financial distress. In addition, DA has been employed by Abdou et al. (2008), Abdou (2009a), Akkoc (2012), Bardos (1998), Desai et al. (1996), Lee et al. (2002, 2006), Lee and Chen (2005), Martell and Fitts (1981), Min and Lee (2008), Mylonakis and Diacogiannis (2010), Overstreet et al. (1992) and Reichert et al. (1983) to build credit scoring models. In the field of banking, Öğüt et al. (2012) used DA to predict BFSRs issued by Moody's.

3.3.7.2 Discriminant, content and construct validity

The effectiveness of DA and the resulting discriminant models require a test for discriminant validity, content and construct validity (Podsakoff and Oragan, 1986). In this case, the classification as well as the use of bank financial and nonfinancial variables provides distinctive dimensionality, which means that the issue of discriminant validity is well settled.

Regarding the issues of content and construct validity, the characteristics of bank financial variables are drawn from relevant literature that adequately provides multidimensional perspectives (e.g., asset quality, capital adequacy, credit risk, liquidity and profitability categories). In addition, these financial variables provide adequate coverage of the important contents and therefore a good basis for content validity (Nunnally, 1994). Because many related studies have conducted empirical examinations of bank financial and nonfinancial variables in the literature of the banking industry, these variables provide an adequate evidence of construct validity (Dince and Fortson, 1972;Sinkey, 1975).

3.3.8 Logistic regression

LR is a well-established multivariate statistical technique used to predict binomial or multinomial outcomes. The initial model formulation of LR was designed for binary classification problems (Crama et al., 1988). LR is used to examine the relationship between binary or ordinal response probability and one or more independent variables. That is, LR is used when the dependent variable is a dichotomy (two categories) and the independents are of any type (Cox and Snell, 1989; Hosmer and Lemeshow, 2000).

LR is a progression of the ordinary multivariate linear regression. The main difference between logistic and linear regression is that the dependent variable is binary or dichotomous. Consequently, the chosen parametric models and the assumptions attributed to each technique are different. Once these differences are accounted for, the methods used in an LR analysis pursue the same general principles used in linear regression (Hosmer and Lemeshow, 2000). LR is different from other classification techniques in that it thoroughly analyses a major subset of variable combinations to explain the positive and negative nature of the observations (e.g., to describe high-FSR or low-FSR banks, solvent or insolvent banks; Hammer et al., 2012).

The coefficient generated by LR for each independent variable explains the contribution of that variable to variations in the dependent variable. However, the dependent variable can only be defined by two values: 0 or 1. The nature of the dependent variable is the main difference between linear and logistic regression. In linear regression, the outcome of regression predicts a numerical value of the dependent variable from relevant independent variables and coefficients. In logistic regression, the result predicts the probability (p) that it is 1 rather than 0 (i.e., the event/person fits in one group rather than the other).

Consequently, the log transformation of the p values is employed to normalise the distribution and thus create a link with the linear regression equation. This process also is known as *logit of* p or *logit (p)*. *Logit (p)* is the log (to base *e*) of the odds ratio or likelihood ratio that the dependent variable is 1 and can be defined as follows:

$$\text{Logit (p)} = \log[p / (1 - p)] = \ln[p / (1 - p)] \tag{11}$$

where p is the range from 0 to 1, the *Logit (p)* scale ranges from negative infinity to positive infinity. LR uses binomial probability theory to develop a logit model that is derived from linear regression. The logit model is described in the following equation (Abdou et al., 2008):

$$\text{Log}[\frac{p}{1-p}] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{12}$$

where p is the probability of the outcome of interest, α is the constant of the equation and β_i is the coefficient in the linear combination of independent variables, X_i, for i = 1 to n. LR finds a best-fit equation using the maximum likelihood method instead of the least-squared deviations method used for linear regression (Freund et al., 2006). The maximum likelihood method maximises the probability of getting the observed results into the appropriate category given the fitted regression coefficients. Consequently, the following nonlinear function is used to express the relationship between independent variables and binary dependent variable (Canbas et al., 2005; Premachandra et al., 2009):

$$P(Z_i) = \frac{e^{Z_i}}{1+e^{Z_i}} = \frac{1}{1+e^{-Z_i}} \tag{13}$$

where $P(Z_i)$ is a cumulative probability function that takes values between 0 and 1; and

$$Z_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{14}$$

Thus the objective of LR is to predict banks' FSR group memberships correctly for individual observations using the most prudent model. A model is developed based on the inclusion of all independent variables that are valid in predicting the dependent variable, namely, banks' FSR group memberships.

In the literature of finance, LR is a widely used technique among practitioners to predict corporate and bank failure (Boyacioglu et al., 2009; Brezigar-Masten and Masten, 2012; Canbas et al., 2005; Doğanay et al., 2006; Hua et al., 2007; Jones and Hensher, 2004; Kick and Koetter, 2007; Kolari et al., 2002; Lanine and Vennet, 2006; Li et al., 2010;Loannidis et al., 2010; Martin, 1977; Ohlson, 1980; Premachandra et al., 2009; Zhao et al., 2009); credit ratings (Chaveesuk et al., 1999; Ederington, 1985; Kim et al., 1993; Kim and Ahn, 2012; Maher and Sen, 1997; Oelerich and Poddig, 2006; Tsai and Chen, 2010) and credit scoring models (Abdou, 2009a; Abdou et al., 2008; Akkoc, 2012; Desai et al., 1996; Joanes, 1993; Laitinen, 1999; Lee et al., 2002, 2006; Lee and Chen, 2005; Ruo-wei and Chun-yang, 2007; West, 2000; Westgaard and Wijst, 2001; Wiginton, 1980). Finally, the LR model has been employed by Öğüt et al. (2012), Hammer et al. (2012), Poon et al. (1999), and Belloti et al. (2011a, 2011b) to predict BFSRs.

3.4 Conclusion

This chapter presents and justifies the research method used in this thesis to fulfill the research objectives. This study has followed positivism as research philosophy because it depends entirely on application of various statistical techniques to a large set of quantitative data to test certain designated hypotheses to achieve the research objectives.

This chapter starts by explaining the data collection process via Bank scope database. The researcher divided the dataset into three samples: entire dataset, $subsample_1$ and $subsample_2$. This is followed by a description of the numerical rating of the dependent variable (i.e., bank FSR issued by CI) and categorises the FSRs into four quartiles (i.e., high FSR, near-high FSR, low FSR and near-low FSR). In addition, bank financial performance variables are elucidated thoroughly (i.e., asset quality, capital adequacy, credit risk, liquidity and profitability categories) along with the designated proxies that belong to each category and the expected sign associated with each proxy for bank FSR. Finally, a list of control variables is introduced to control for bank financial performance variables (i.e., country effect, size effect, time effect and SR).

The ultimate goal of this thesis is to enhance the performance of banks in the Middle East region by identifying the main financial and nonfinancial variables associated with high- and near-high FSRs using publicly available data. Consequently, the ML technique is introduced to achieve this goal. This thesis is intended to provide the banking sector in the Middle East region with a vast range of different bank FSR group membership modeling techniques (i.e., CHAID, CART, MLP neural networks, DA and LR) and to evaluate the predictive capability of these models using various evaluation criteria (i.e., ACC, EMC and gains charts). The key challenge is to build bank FSR group membership models to increase classification and prediction accuracy and to reduce the misclassification costs. The following two chapters introduce and interpret the empirical results.

CHAPTER 4 : MULTINOMIAL LOGIT (ML) RESULTS

4.1 Introduction

In this chapter, the researcher reports the results that identify the main bank performance measures (i.e., financial and nonfinancial variables) associated with high- and near-high FSRs versus low- and near-low FSRs in the Middle East region. The results of ML technique are presented in the following order: (1) descriptive statistics and (2) results obtained from the various models (i.e., asset quality, capital adequacy, credit risk, liquidity, profitability) and (3) all financial category models (with and without dummies).

4.2 Descriptive statistics

Appendices B, C and D display the descriptive statistics tables for FSRs and all explanatory variables (financial and nonfinancial) for low- and near-low-FSR banks; high- and near-high-FSR banks and for all four quartiles of FSR banks in the Middle East region. As shown in appendix B, the mean FSR for low- and near-low-FSR banks is 10.62. This indicates that most of low- and near-low-FSR banks in the Middle East region are assigned BBB^- ratings. This is similar to the values of median and mode. The standard deviation of the FSR is 1.554, which means that low- and near-low-FSR banks are not highly dispersed.

Appendix C shows that the mean FSR for high- and near-high-FSR banks is 14.824. This indicates that majority of high- and near-high-FSR banks in the Middle East region are assigned an A rating. This is consistent with the values of median and mode. Also, the standard deviation is 1.118, which means that there is not a large gap between high- and near-high-FSR banks. It is noteworthy that the mean for all four quartiles of bank FSRs is 12.678, which corresponds to a BBB rating. This finding indicates that most of rated banks in the Middle East are assigned a BBB rating, which is confirmed by median and mode values. The higher standard deviation (2.503) than the other two subsamples indicates high dispersion of FSRs across all banks in the Middle East.

4.3 ML results

The researcher used ML because the characteristics of the model fit both the objective of the study and the characteristics of the data. The researcher performed a separate regression run for each financial performance category (Model 1) and another run that added the nonfinancial variables to each category (Model 2) to examine their relative explanatory power for banks' FSRs. Finally, the researcher conducted regression runs for the overall financial performance categories (with and without nonfinancial variables) to examine the overall explanatory power for banks' FSRs. The bank performance financial categories are classified as asset quality, capital adequacy, credit risk, liquidity and profitability.

Tables 4.1, 4.4, 4.7, 4.10, 4.13 and 4.16 show the overall fitting for each model. The χ^2 for each variable indicates its significance (based on Likelihood Ratio Test) over various bank ratings using forward stepwise algorithm which guarantees entering the significant variable in each subsequent run[45]. The reported variables in each model represent the significant predictors that explain the change in the dependent variables (bank FSRs) which is measured by the probability of moving from a current to subsequent bank FSRs (Greene, 2000; Studenmund, 2001and Verbeek, 2012).

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[45] Forward stepwise method is defensible under certain conditions, such as: (1) no previous research exists on which to base the hypothesis for testing, and (2) when causality is not of interest and the researcher merely wishes to find a model that fits data.

4.3.1 Asset quality models

Table 4.1: Asset quality results for ML model with and without bank FSR dummies[46]

Variables	Model 1 without dummies[47]		Model 2 with dummies[48]	
	χ^2	*df*	χ^2	*df*
Intercept	44.73^{***}	10	132.19^{***}	10
CS	40.02^{***}	10	30.26^{***}	10
LLRIL	35.54^{***}	10	19.32^{**}	10
ILGL	186.95^{***}	10	79.53^{***}	10
LLPNIR	37.82^{***}	10	34.05^{***}	10
Size			169.62^{***}	10
SR			137.15^{***}	10
No. of observations	503		506	
χ^2	415.7^{***}		726.0^{***}	
Log Likelihood	0.001744^{***}		0.001446^{***}	
(Pseudo)[1] R^2	57.0%		77.2%	
Overall classification accuracy	35.2%		40.1%	

Note. Multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 are excluded. Outliers are also excluded. *, **, and ***denote a statistically significant difference at 10%, 5% and 1% levels, respectively.
[1]The researcher reports the value of Nagelkerke, which is an adjustment to Cox and Snell measure.

As shown in Table 4.1, the first run (Model 1) includes the main explanatory (financial) variables in the asset quality category. The second run (Model 2) includes the main explanatory variables in addition to non-financial variables (dummy variables) that control for sovereign ratings, size, country and time. As previously mentioned, FSRs is divided into four quartiles: (1) the first quartile ranges from B to BBB$^-$ ratings and representing low-FSR banks in the Middle East region; (2) the second quartile consists of only BBB ratings, which corresponds to near-low-FSR banks; (3) the third quartile includes BBB$^+$ and A$^-$ ratings, which indicate near-high-FSR banks; and (4) the fourth quartile identifies high-FSR banks with ratings that range from A to AA$^-$. The results show that the two models approximate the

[46] NCONIBLLP and UILE are excluded from both models because of a large number of missing observations.
[47] ILGL and ILE variables are highly correlated at 82.3%. The researcher included ILGL and removed ILE from the ML regression model. This is mainly because the regression model Pseudo R-square with ILGL is 57.0% but it is only 46.2% with ILE instead of ILGL. All of the results are available from the researcher.
[48] Country and SR are highly correlated at 81.7%. The researcher ran the model several times and finally concluded that it was advantageous to remove the country dummy variable and keep SR.

behaviour of data for Middle East banks fairly as far as the two models are significant at 1% level. Therefore, the two models outperform the null. The detailed statistical characteristics of the asset quality category (with and without dummies) are as follows:

(1) As presented in Table 4.1, forward stepwise regression results show that four statistically significant predictors are included in Model 1. Four predictors are statistically significant at the 1% level: total equity to total assets (proxy for bank CS), loan loss reserve to impaired loans (LLRIL), impaired loans to gross loans (ILGL) and loan loss provision to net interest revenue (LLPNIR). For Model 2, the results show that six statistically significant predictors are included in the final model: five (CS, ILGL, LLRNIR, SR and size) are statistically significant at the 1% level and one (LLRIL) is statistically significant at the 5% level.[49]

(2) For Models 1 and 2, goodness-of-fit shows that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This means that the two models adequately fit the data.

(3) Regarding the explanatory power of Model 1 (pseudo R-square), the results show that four significant predictors account for 57% of FSR variations in the probability of moving from a current to subsequent bank FSR. For Model 2, the results show that six significant predictors account for 77.2% of FSR variations in the probability of moving from a current to subsequent bank FSR.

[49] It is worth mentioning that the researcher ran the ML regression using the first and fourth quartiles for the asset quality category. The number of observations for Models 1 and 2 are 294 and 297, respectively. For Model 1, the results show that four significant predictors (CS, LLRIL, ILGL and LLPNIR) account for 68.4% of FSR variations. Furthermore, the cross classification matrix shows that the asset quality category under Model 1 classifies 50.7% of predicted FSR correctly and that it is relatively powerful in predicting B and A ratings that correspond to 100% and 70.7 %, respectively. For Model 2, the results show that five significant predictors (CS, ILGL, LLPNIR, size and SR) account for 82.3% of FSR variations. The cross-classification matrix shows that this category under Model 2 classifies 52.2% of predicted FSRs correctly and that this model is relatively powerful in predicting A, B and BBB- ratings that correspond to 80.6%, 66.7% and 62.7%, respectively. Detailed results are available upon request.

(4) Regarding the classification power of asset quality for Model 1, the results show that this category classifies 35.2% of predicted FSR as correct. Furthermore, the cross-classification matrix shows that the asset quality category for Model 1 is relatively powerful in predicting B, A and BBB ratings that correspond to 100%, 73.2 % and 67%, respectively. Regarding Model 2, the results show that the asset quality category with dummies classifies 40.1% of predicted FSRs correctly. Model 2 is relatively powerful in predicting B, BBB and A ratings that correspond to 66.7%, 62.1% and 58.2%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant asset quality predictors that are associated with each bank rating individually. That is, Table 4.1 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant asset quality predictors that help increasing the probability of moving from a current to a higher FSR.

Table 4.2 shows that the parameters of estimates of B, BB-, BB, BB+ and BBB-, BBB, BBB+, A- and A+ ratings are most representative for Model 1 and the available data. The parameters of final predictors (1) CS, (2) LLRIL, (3) ILGL and (4) LLPNIR vary in their significance across different FSRs. Table 4.3 shows that the parameters of estimates of B, BB-, BB, BB+, BBB- , BBB, BBB+, A- and A ratings are most representative for Model 2 and the available data. The parameters of final predictors (1) CS, (2) LLRIL, (3) ILGL, (4) LLPNIR, (5) size and (6) SR vary in significance.

Table 4.2: Parameter estimates for the asset quality model without dummies (Model 1)

FSR	Variables	B	Std. Error	Wald	df	Sig.
6 (B)	ILGL	122.553	38.873	9.939	1	.002
8(BB-)	ILGL	70.605	16.633	18.018	1	.000
9(BB)	LLPNIR	4.972	2.399	4.296	1	.038
	ILGL	74.376	16.461	20.415	1	.000
	CS	-14.902	9.147	2.654	1	.100
10(BB+)	LLRIL	-3.278	.890	13.568	1	.000
	ILGL	63.367	16.296	15.120	1	.000
	CS	-13.568	7.508	3.265	1	.071
11(BBB-)	ILGL	64.117	16.220	15.626	1	.000
	CS	-18.185	6.875	6.997	1	.008
12(BBB)	LLRIL	-1.363	.481	8.018	1	.005
	ILGL	48.640	16.134	9.089	1	.003
	CS	-13.863	6.579	4.440	1	.035
13 (BBB+)	ILGL	-36.094	16.771	4.632	1	.031
14(A-)	ILGL	-48.075	16.165	8.845	1	.003
16(A+)	ILGL	-28.481	16.875	2.848	1	.091

Table 4.3: Parameter estimates for the asset quality model with dummies (Model 2)

FSR	Variables	B	Std. Error	Wald	df	Sig.
6(B)	SR	-2.089	.562	13.824	1	.000
	LLPNIR	6.260	3.922	2.548	1	.100
	ILGL	35.515	14.948	5.645	1	.018
8(BB-)	SR	-.988	.241	16.765	1	.000
	LLPNIR	4.297	2.640	2.649	1	.100
	ILGL	23.551	14.318	2.705	1	.100
9(BB)	SR	-.996	.222	20.199	1	.000
	ILGL	26.870	14.062	3.651	1	.056
10(BB+)	SR	-.860	.207	17.283	1	.000
	LLRIL	-2.310	.978	5.574	1	.018
	ILGL	23.159	13.948	2.757	1	.097
	Size	-5.494	.950	33.450	1	.000
11(BBB-)	SR	-.994	.202	24.284	1	.000
	CS	-20.565	9.740	4.457	1	.035
	LLPNIR	5.727	2.227	6.613	1	.010
	Size	-4.465	.874	26.070	1	.000
12(BBB)	SR	-.738	.194	14.420	1	.000
	LLRIL	-1.191	.560	4.523	1	.033
	LLPNIR	4.557	2.195	4.309	1	.038
	Size	-4.613	.850	29.487	1	.000
13(BBB+)	SR	.512	.203	6.374	1	.012
	LLPNIR	-5.759	2.172	7.031	1	.008
	Size	4.359	.869	25.141	1	.000
14(A-)	LLPNIR	-3.678	2.107	3.049	1	.081
	Size	2.741	.824	11.057	1	.001
15 (A)	SR	.401	.189	4.524	1	.033
	LLPNIR	-4.941	2.090	5.590	1	.018
	Size	2.807	.815	11.854	1	.001

As reported in Tables 4.2 and 4.3, the significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant asset quality predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using asset quality predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile. That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

Table 4.2 shows that CS has a negative and statistically significant coefficient at the 1% level for a BBB- rating, at the 5% level for BBB ratings and at the 10% level for BB and BB+ ratings. In line with Pasiouras et al. (2006, 2007), the negative sign associated with predictor estimates indicates that low- and near-low-FSR banks in the Middle East are undercapitalised. As shown in Table 4.3, CS has a negative and statistically significant coefficient at the 5% level for a BBB- rating. This finding is in harmony with results reported earlier.

In Table 4.2, ILGL has positive and statistically significant coefficients at 1% level for low- and near-low FSRs (i.e., B, BB-, BB, BB+, BBB- and BBB ratings). Also, ILGL has negative and statistically significant coefficients at the 1% level for an A- rating, at the 5% level for a BBB+ rating and at the 10% level for an A+ rating. This finding explains the relative importance of this ratio in regard to FSR assignment. The positive sign associated with predictor estimates denotes that higher impaired loans to gross loans leads to deterioration of bank asset quality and thus lower FSRs are assigned. This result confirms the theoretical assumption of banking activity. This finding may reflect peculiarities of bank financing in the

Middle East. That is, banks in the Middle East used to sell loans (mostly uncollateralised) according to governmental directions. This resulted in accumulated loans (mostly nonperforming) over the years. On the contrary, the negative sign associated with predictor estimates concludes that high- and near-high-FSR banks are more conservative and careful about selling loans. This approach yields a relatively lower impaired loan to gross loan ratio and consequently better asset quality and loan portfolio value. This argument is supported by the evidence that the average rate of ILGL for low- and near-low-FSR banks (14%) is much higher than that for high- and near-high-FSR banks (4%)[50] (see appendix B and C, respectively). In Table 4.3, ILGL has positive and statistically significant coefficients at the 5% level for B ratings and at the 10% level for BB- , BB and BB+ ratings. This finding is similar to results reported for Model 1.

Table 4.2 indicates that LLRIL has a negative and statistically significant coefficient at the 1% level for BB+ and BBB ratings. The negative sign associated with predictor estimates concludes that low- and near-low-FSR banks in the Middle East are not accumulating adequate balances of loan loss reserves to compensate for the increase in non-performing loans. Consequently, investor confidence concerning bank asset quality deteriorates and thus negatively affects banks' assigned FSRs. This is supported by the fact that average rate of LLRIL for high- and near-high-FSR banks (139%) is relatively higher than for low- and near-low FSR banks (90.4%)(see appendix C and B, respectively). Table 4.3 shows that LLRIL has a negative and statistically significant coefficient at the 5% level for BB+ and BBB ratings. This finding is compatible with results reported for Model 1.

As indicated in Table 4.2, LLPNIR has positive and statistically significant coefficients at the 5% level for BB ratings. The positive sign associated with predictor estimate indicates that

[50] It is also worth noting that the average rate of ILGL for low-FSR banks (19.28%) is much higher than the average rate for high-FSR banks (3.06%).

low-FSR banks in the Middle East have an increasing amount of loan loss provision relative to net interest revenue generated. Low-FSR banks are accepting highly risky loans without being properly compensated by margins. Accordingly, bank asset quality deteriorates, which negatively affects assigned FSRs. This finding is intuitive and consistent with Van-Roy (2006) and Pasiouras et al. (2006). Table 4.3 specifies that LLPNIR has positive and statistically significant coefficients at the 1% level for BBB- ratings, at the 5% level for BBB and at the 10% level for B and BB- ratings. Furthermore, LLPNIR has a negative and statistically significant coefficient at the 1% level for BBB+ ratings, at the 5% level for A ratings and 10% level for A- ratings. The negative sign associated with predictor estimates denotes that high- and near-high-FSR banks in the Middle East are well-run banks in the sense that they compensate highly risky loans with greater interest margins. However, the positive sign associated with predictor estimates validates results reported for Model 1. Finally, this argument is supported by the fact that average rate of LLPNIR for low- and near-low-FSR banks (26.7%) is higher than the same average for high- and near-high-FSR banks (17.4%)[51] (see appendix B and C , respectively).

As seen in Table 4.3, SR has negative and statistically significant coefficients at the 1% level for B, BB-, BB, BB+, BBB- and BBB ratings. Moreover, SR has positive and statistically significant coefficient at the 5% level for BBB+ and A ratings. The negative sign associated with predictor estimates signifies that banks operating in countries with low SRs are assigned low- and near-low FSRs. On the other hand, the positive sign associated with predictor estimates indicates that banks operating in countries with high SRs are assigned high- and near-high FSRs. It is worth noting that the average SR associated with low- and near-low-FSR banks is 10.776, which corresponds to a BBB- SR; and high- and near-high-FSR banks

[51] The average rate of loan loss provisions to net interest revenue for low-FSR banks (34.32%) is much higher than the average rate for high-FSR banks (16.27%).

operate in countries with an average SR of 14.932, which correspond to an A SR (see appendix B and C, respectively). These findings confirm that CI identifies the relative impact of macroeconomic variables and the surrounding environment on the overall performance of banks, which eventually affects their FSRs. This finding is intuitive and consistent with results reported by (Belloti et al., 2011a; Poon and Firth, 2005; Poon, et al. 2009; Van-Roy, 2006)[52] .

Table 4.3 shows that size has negative and statistically significant coefficients at the 1% level for BB+, BBB- and BBB ratings. Moreover, size has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. The positive sign associated with predictor estimates indicates that large size banks are assigned high- and near-high FSRs. This finding complies with results reported by (Belloti et al., 2011a; Pasiouras et al., 2006; Poon and Firth, 2005; Van-Roy, 2006). This result confirms that large banks are generally stronger as they may be more diversified (Demsetz and Strahan, 1997) and thus are better able to survive shocks; in addition, many investors believe in the existence of the too-big-to-fail assumption, which presumes that troubled large banks must be bailed out by governments because of their systemic importance to the country’s economic stability (Laere et al., 2012).

On the contrary, the negative sign associated with predictor estimates implies that small banks are assigned low- and near-low FSRs. This argument is supported by the fact that average bank size for low- and near-low-FSR banks (1.417) is smaller than the average bank size for high- and near-high-FSR banks (2.381) (see appendix B and C, respectively). It is also worth noting that large banks have a stronger capacity to access new capital markets to

[52] Poon et al. (2009) assumed two hypotheses about the effect of country SRs on bank tendency to seek bank ratings. The two hypotheses are the certification hypothesis and counter-certification hypothesis. The former assumes that banks located in countries with low SRs will seek higher ratings to reduce the information asymmetry problem. Thus, certification from rating agencies will resolve such asymmetry problems. On the contrary, the latter hypothesis assumes that countries with low SRs are characterised by poor legal systems and disclosure environments. Thus, rating agency decisions are affected negatively. That is, banks located in countries with low SRs are probably assigned low ratings.

overcome any unexpected liquidity problems (Konishi and Yasuda, 2004). In line with this, Pettit et al. (2004) stated, ‘Larger companies tend to have higher credit ratings’ and that ’size metrics offer the strongest statistical correlation with credit ratings—reflecting important qualitative factors such as geographic and product market diversification, competitive position, bargaining power, market share and brand stature power, market share and brand stature’ (p. 9).

4.3.2 Capital adequacy models

Table 4.4: Capital adequacy results for the ML model with and without bank FSR dummies [53]

Variables	Model 1 without dummies		Model 2 with dummies[54]	
	χ^2	*df*	χ^2	*df*
Intercept	58.83***	11	248.7***	11
CS	100.9***	11	42.59***	11
ENL	126.3***	11	56.06***	11
TCR	53.59***	11	61.84***	11
EM	51.50***	11		
Size			305.2***	11
SR			115.3***	11
T			122.5***	11
No. of observations	496		496	
χ^2	309.0***		827.5***	
Log Likelihood	0.001829***		0.001321***	
(Pseudo)[1] R^2	47%		82.2%	
Overall classification accuracy	33.3%		45.8%	

Note. Multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 are excluded. Outliers are also excluded. *, **, and ***denote a statistically significant difference at 10%, 5% and 1% levels, respectively.

[1]The researcher reports the value of Nagelkerke, which is an adjustment to Cox and Snell measure.

(1) As shown in Table 4.4, forward stepwise regression[55] results show that four statistically significant predictors are included in Model 1. The four predictors are statistically significant at the 1% level, which is total equity to total assets (CS), the ratio of equity to net loans (ENL), total capital ratio (TCR) and equity multiplier (EM). For Model 2, the results show that six significant predictors are

[53] TR, CFTA, CFNL, CFDSTF, CFL and SDCF are excluded from both models because of large numbers of missing observations.

[54] SR and Country dummy variables are highly correlated at 73.4%. The researcher performed the regression run with the SR variable alone, the pseudo R-square was 82.2% .The researcher conducted another regression run with Country dummy variable alone, and pseudo R-square was 70.4%. Thus, the researcher included the SR variable and dropped the country dummy variable for the final ML regression run for this category.

[55] The researcher ran the ML regression using first and fourth quartile data for the capital adequacy category. The number of observations for Models 1 and 2 were 298 and 296, respectively. For Model 1, the results show that four statistically significant predictors (CS, ENL, TCR and EM) accounted for 56.9% of FSR variations. Furthermore, the cross-classification matrix shows that the capital adequacy category for Model 1 classifies 48% of predicted FSRs correctly and that it is relatively powerful in predicting A ratings at 92.1%. For Model 2, the results show that six statistically significant predictors (CS, TCR, ENL, time effect, size and SR) accounted for 89% of FSR variations. The cross-classification matrix shows that this category of Model 2 classifies 60.8% of predicted FSRs correctly and that this model is relatively powerful in predicting B, BBB- and A ratings with 100%, 75% and 73.3%, respectively. Detailed results are available upon request.

included in final model. The six predictors, CS, TCR, ENL, SR, size and time effect (T), are statistically significant at the 1% level.

(2) For Model 1, the statistical characteristic of model fitting shows that final model is significant at 1% level (χ^2 = 309.03, df = 44) and so outperforms the null. For Model 2, the statistical characteristic of model-fitting shows that final model is significant at the 1% level (χ^2 = 827.47, df = 66) and consequently outperforms the null.

(3) For Models 1 and 2, the goodness-of-fit shows that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This means that the two models are fitting data.

(4) For Model 1, the researcher reports the value of Nagelkerke for the explanatory power of the model (pseudo R-square). The results show that four significant predictors account for 47% of FSR variations in the probability of moving from a current to subsequent bank FSR. For Model 2, the results show that six significant predictors account for 82.2 % of FSR variations in the probability of moving from a current to subsequent bank FSR.

(5) For Model 1, the classification power of capital adequacy is of great interest. The results show that this category classifies 33.3% of predicted FSRs correctly. It is also noteworthy that the cross-classification matrix shows that the capital adequacy category is powerful in predicting A ratings that correspond to 73.3%. For Model 2, the results show that the capital adequacy category with dummies classifies 45.8% of predicted FSR correctly. Additionally, Model 2 is relatively powerful in predicting B, BBB and BB+ ratings that correspond to 100%, 63.9% and 61.1%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant capital adequacy predictors that are associated with each bank rating individually. That is, Table 4.4 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant capital adequacy predictors that help increasing the probability of moving from a current to a higher FSR.

Table 4.5 indicates that the parameters for estimates of B, B+, BB–, BB, BB+, BBB-, BBB, BBB+, A- , A and A+ ratings are best representative for Model 1 and the available data. The parameters of final predictors CS, ENL, TCR and EM vary in their significance across different FSRs. Table 4.6 shows that the parameters estimates of B+, BB-, BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings are most representative for Model 2 and the available data. The parameters of the final predictors, CS, ENL, TCR, size, SR and time effect (T), vary in their significance across different ratings.

Table 4.5: Parameter estimates for the capital adequacy model without dummies (Model 1)

FSR	Variables	B	Std. Error	Wald	df	Sig.
6 (B)	EM	.567	.149	14.494	1	.000
	CS	-68.589	19.351	12.564	1	.000
	ENL	-11.248	4.123	7.442	1	.006
7(B+)	EM	.608	.168	13.074	1	.000
8(BB-)	EM	.525	.211	6.174	1	.013
9 (BB)	TCR	-19.697	7.579	6.754	1	.009
	ENL	-6.541	3.139	4.343	1	.037
10(BB+)	CS	-19.019	8.290	5.263	1	.022
	TCR	-12.002	7.195	2.783	1	.095
11(BBB-)	EM	.633	.152	17.350	1	.000
	CS	-32.087	11.100	8.357	1	.004
	ENL	-6.422	3.045	4.449	1	.035
12(BBB)	EM	.625	.152	16.909	1	.000
	CS	-41.129	11.073	13.797	1	.000
	TCR	-16.990	6.946	5.983	1	.014
13(BBB+)	EM	.459	.202	5.151	1	.023
	CS	37.598	14.566	6.663	1	.010
	TCR	16.380	7.837	4.368	1	.037
14(A-)	EM	.397	.184	4.659	1	.031
	CS	31.442	13.129	5.736	1	.017
15(A)	EM	.617	.152	16.432	1	.000
	CS	41.637	11.335	13.494	1	.000
	TCR	24.340	6.976	12.174	1	.000
	ENL	12.920	3.637	12.623	1	.000

16(A+)	EM	.285	.138	4.256	1	.039
	TCR	14.877	7.832	3.608	1	.057
	ENL	8.001	4.324	3.423	1	.064

Table 4.6: Parameter estimates for the capital adequacy model with dummies (Model 2)

FSR	Variables	B	Std. Error	Wald	df	Sig.
7(B+)	SR	-2.342	.826	8.041	1	.005
	T	1.219	.527	5.354	1	.021
	Size	-5.277	2.127	6.153	1	.013
8(BB-)	SR	-2.177	.530	16.879	1	.000
	TCR	-57.966	25.433	5.195	1	.023
	T	1.159	.315	13.511	1	.000
9(BB)	SR	-1.508	.421	12.844	1	.000
	CS	-37.548	17.929	4.386	1	.036
	T	1.542	.266	33.644	1	.000
	Size	-9.806	1.491	43.231	1	.000
10(BB+)	SR	-1.900	.414	21.009	1	.000
	CS	-31.363	17.721	3.132	1	.077
	T	1.703	.245	48.239	1	.000
	Size	-8.998	1.102	66.658	1	.000
11(BBB-)	SR	-1.831	.408	20.183	1	.000
	T	1.074	.223	23.125	1	.000
	Size	-6.731	1.005	44.852	1	.000
12(BBB)	SR	-1.795	.404	19.697	1	.000
	T	1.012	.214	22.379	1	.000
	Size	-6.218	.975	40.675	1	.000
13(BBB+)	SR	1.527	.409	13.925	1	.000
	T	1.132	.222	25.987	1	.000
	Size	6.102	.998	37.357	1	.000
14(A-)	SR	1.231	.401	9.415	1	.002
	T	.669	.206	10.519	1	.001
	Size	4.269	.945	20.398	1	.000
15(A)	SR	1.285	.398	10.416	1	.001
	TCR	19.658	9.625	4.171	1	.041
	ENL	14.600	6.339	5.304	1	.021
	T	.689	.202	11.629	1	.001
	Size	3.754	.935	16.134	1	.000
16(A+)	TCR	20.773	10.350	4.028	1	.045

As shown in Tables 4.5 and 4.6, the reported significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant capital adequacy predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using capital adequacy predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile.

That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

As shown in Table 4.5, CS has negative and statistically significant coefficients at the 1% level for B, BBB- and BBB ratings and at the 5% level for BB+ ratings. Also, CS has a positive and statistically significant coefficient at the 1% level for BBB+ and A ratings and at the 5% level for A- ratings. This finding is in line with results reported by Pasiouras et al. (2006, 2007), Belloti et al. (2011a) and Chen (2012). The negative sign associated with predictor estimates indicates that low- and near-low-FSR banks are undercapitalised. On the contrary, the positive sign associated with the predictor estimates implies that high and near-high-FSR banks are well capitalised. This debate is supported by the fact that the average rate of CS ratio associated with high- and near-high-FSR banks (12.5%) is higher than the same average rate associated with low- and near-low-FSR banks (10.9%) (see appendix C and B, respectively). Moreover, Table 4.6 indicates that CS has a negative and statistically significant coefficient at the 5% level for BB ratings and at the 10% level for BB+ ratings. This finding confirms results reported for Model 1.

As shown in Table 4.5, ENL has a negative and statistically significant coefficient at the 1% level for B ratings and at the 5% level with BB and BBB- ratings. On the other hand, ENL has a positive and statistically significant coefficient at the 1% level for A ratings and at the 10% level for A+ ratings. The negative sign associated with the predictor estimates denotes that low-FSR banks are undercapitalised. Furthermore, the positive sign associated with predictor estimates indicates that high-FSR banks are well capitalised. In line with this, the average rate of ENL for low-FSR banks (22.5%) is lower than average rate of ENL for high-FSR banks (39.5%). This requires further investigation and development to identify the main credit characteristics of low-FSR banks in the Middle East.

Apparently, low-FSR banks are selling more loans (although mostly non-performing) without compensating with available equity. Conversely, high-FSR banks are concerned about equity accumulation to withstand expected future credit risk problems. As shown in Table 4.6, ENL has a positive and statistically significant coefficient at the 5% level for A ratings. The positive sign associated with the predictor estimate confirms the results reported for Model 1. As previously mentioned, it seems that managers of high-FSR banks are more firm and strict about maintaining the appropriate amount of equity cushion to absorb expected losses on their loan books. This finding validates results reported by Poon et al. (2009).[56]

Table 4.5 shows that TCR has negative and statistically significant coefficients at the 1% level for BB ratings, at the 5% level for BBB ratings and at the 10% level for BB+ ratings. Also, TCR has a positive and statistically significant coefficient at the 1% level for A ratings; at the 5% level for BBB+ ratings and at the 10% level for A+ ratings. The signs associated with the predictor estimates confirm results reported under the CS category. Specifically, mangers of low- and near-low-FSR banks in the Middle East are not capable of mitigating high risk weighted assets by increasing Tier 1 and Tier 2 bank capital. On the contrary, high- and near-high-FSR banks are maintaining an adequate level of TCR to satisfy Basel I and II requirements.

This debate is supported by the fact that the average rate of TCR associated with high- and near-high-FSR banks (20.8%) is higher than average rate of TCR associated with low- and near-low-FSR banks (10%) (see appendix B and C, respectively). In line with this, Table 4.6 indicates that TCR has a negative and statistically significant coefficient at the 5% level for BB- ratings. Also, TCR has a positive and statistically significant coefficient at the 5 % level

[56] Poon et al. (2009) reported that solicited banks (i.e., with higher ratings in general than other unsolicited banks) have a higher average mean of equity to total loans ratio than that of unsolicited banks.

for high A and A+ ratings. This finding confirms that low-FSR banks in the Middle East are undercapitalised and that high-FSR banks are paying more attention to TCR

Table 4.5 reveals that EM has a positive and statistically significant coefficient at the 1% level for B, B+, BBB- , BBB and A ratings and at the 5% level for BB-, BBB+, A- and A+ ratings. The positive sign associated with the predictor estimates provides further evidence that EM matters apart from FSRs assigned by CI. This finding confirms that banks in the Middle East are relying more on debt (i.e., deposits) to finance their assets rather than equity regardless of the assigned FSR. This finding is intrinsic to the banking industry in the Middle East in light of the historical evolution of the banking industry from governmental funds. Specifically, the contribution of public equity has emerged recently according to openings and the progress or pace of stock markets in the region.

Table 4.6 shows that time effect (T) has positive and statistically significant coefficients at the 1% level for BB-, BB, BB+, BBB-, BBB, BBB+, A- and A ratings and at the 5% level for B+ ratings. This finding implies that there was a slight improvement in bank FSRs during period from 2001 to 2009. This is supported by the fact that the banking sector in the Middle East region has not been significantly affected by the financial crises because of their limited integration into the global financial crises. In addition, many banks have employed robust lending decisions that resulted in a credit dry-out (Kouame, 2009).

As indicated in Table 4.6, size has negative and statistically significant coefficients at the 1% level for BB, BB+, BBB- and BBB ratings and at the 5% level for B+ ratings. In addition, size has a positive and statistically significant coefficient at 1% level for BBB+, A- and A ratings. This finding is in line with results reported for the asset quality category. Namely, banks with high- and near-high FSRs are larger in size than banks with low- and near-low FSRs in the Middle East region.

Table 4.6 shows that SR has negative and statistically significant coefficients at the 1% level for B+, BB-, BB, BB+, BBB- and BBB ratings. Additionally, SR has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. This finding is similar to results reported for the asset quality category. The positive sign associated with the predictor estimates implies that banks with high- and near-high FSRs are mainly located in countries with high SRs. On the contrary, the negative sign associated with the predictor estimates confirms that banks located in countries with low SRs are assigned low- and near-low FSRs.

4.3.3 Credit risk models

Table 4.7: Credit risk results for ML model with and without bank FSR dummies[57]

Variables	Model 1 without dummies		Model 2 with dummies[58]	
	χ^2	*df*	χ^2	*df*
Intercept	111.0***	11	167.5***	11
CS	46.18***	11	47.80***	11
LLRGL	131.6***	11	171.4***	11
LLRE	70.97***	11		
LLPTL	46.32***	11		
LLPE	47.02***	11		
Size			273.40***	11
SR			156.30***	11
T			120.84***	11
No. of observations	556		556	
χ^2	483.5***		875.3***	
Log Likelihood	0.001970***		0.001578***	
(Pseudo)[1] R^2	58.8%		80.3%	
Overall classification accuracy	33.3%		39.4%	

Note. Multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 are excluded. Outliers also are excluded. *, **, and ***denote a statistically significant difference at 10%, 5% and 1% levels, respectively.

[1]The researcher reports the value of Nagelkerke, which is an adjustment to Cox and Snell measure.

[57] NCOAGL is excluded from both models because of large numbers of missing observations.

[58] SR and the country dummy variable are highly correlated at 73.4%. The researcher performed a regression run with the SR variable alone and the pseudo R-square equals 80.3%. The researcher conducted another regression run with the country dummy variable alone and the pseudo R-square equals 77.5%. Thus, the researcher included the SR variable and dropped the country dummy variable for the final ML regression run for this category.

(1) Results of the forward stepwise regression[59] in Table 4.7 indicate that five significant predictors—total equity to total assets (CS), loan loss reserves to gross loans (LLRGL), loan loss reserves to total equity (LLRE), loan loss provisions to total loans (LLPTL) and loan loss provision to equity (LLPE)—are included in Model 1 and are statistically significant at the 1% level. For Model 2, the results show that five significant predictors—CS, LLRGL, SR, time effect (T) and size effect—are included in the final model and are statistically significant at the 1% level. .

(2) For Model 1, the statistical characteristics of model-fitting show that the final model is significant at the 1% level (χ^2 = 483.456, df = 55) and hence outperforms the null. The same is true for Model 2, in which the statistical characteristics of model-fitting shows that the final model is significant at the 1% level (χ^2 = 875.321, df = 55) and accordingly outperforms the null.

(3) For Models 1 and 2, the goodness-of-fit show that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This confirms that the two models satisfactorily fit the data.

(4) Regarding the explanatory power of Model 1 (pseudo R-square), the results show that five significant predictors account for 58.8% of FSR variations in the probability of moving from a current to subsequent bank FSR. For Model 2, the

[59] The researcher ran the ML regression using first and fourth quartile for the credit risk category. The number of observations for Models 1 and 2 are 341 and 340, respectively. For Model 1, the results show that four statistically significant predictors (CS, LLRGL, LLPTL and LLRE) account for 68.7% of FSR variations. Furthermore, the cross-classification matrix shows that the credit risk category under Model 1 classifies 47.2% of predicted FSRs correctly and that it is relatively powerful in predicting A and B ratings that correspond to 91.5% and 77.8%, respectively. For Model 2, the results show that five statistically significant predictors (CS, LLRGL, time effect, size and SR) account for 86.8% of FSR variations. The cross-classification matrix shows that the credit risk category with dummies classifies 56.2% of predicted FSRs correctly and that this model is relatively powerful in predicting A, B and BBB- ratings that correspond to 81.1%, 77.8% and 65.7%, respectively. Detailed results are available upon request.

results show that five significant predictors account for 80.3% of FSR variations in the probability of moving from a current to subsequent bank FSR.

(5) Regarding the classification power of credit risk for Model 1, the results show that this category classifies 33.3% of predicted FSRs correctly. Furthermore, the cross-classification matrix shows that the credit risk category is relatively powerful in predicting B and A ratings that correspond to 88.9% and 66%, respectively. For Model 2, the results show that the credit risk category with dummies classifies 39.4% of predicted FSR correctly. In line with the asset quality category, Model 2 is relatively powerful in predicting B, BBB and A ratings that correspond to 77.8% , 62.4% and 52.8%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant credit risk predictors that are associated with each bank rating individually. That is, Table 4.7 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant credit risk predictors that help increasing the probability of moving from a current to a higher FSR.

As shown in Table 4.8, the results of the parameter estimates show that B, B+, BB- , BB, BB+, BBB- , BBB, BBB+, A- and A ratings are most representative for Model 1 and the available data. The parameters of final predictors CS, LLRGL, LLRE, LLPTL and LLPE vary in their significance across different FSRs. As shown in Table 4.9, the results of the parameters estimates show that B, B+, BB- , BB, BB+, BBB-, BBB, BBB+, A- and A ratings are most representative for Model 2 and the available data. The parameters of final predictors CS, LLRGL, size, SR and time effect (T) vary in their significance across different FSRs.

Table 4.8: Parameter estimates for the credit risk model without dummies (Model 1)

FSR	Variable	B	Std. Error	Wald	df	Sig.
6 (B)	LLRGL	86.583	27.986	9.572	1	.002
7(B+)	CS	-38.148	20.483	3.469	1	.063
8(BB-)	LLRGL	66.991	26.148	6.564	1	.010
	LLPTL	125.977	78.494	2.576	1	.100
	LLPE	31.748	19.081	2.768	1	.096
9(BB)	LLRGL	61.719	25.357	5.924	1	.015
10(BB+)	LLRGL	75.411	25.278	8.900	1	.003
	LLPTL	196.048	70.840	7.659	1	.006
	LLPE	43.513	18.426	5.577	1	.018
11(BBB-)	LLRGL	71.732	25.300	8.039	1	.005
	LLPTL	171.047	70.293	5.921	1	.015
	CS	-19.195	6.443	8.876	1	.003
	LLPE	41.705	18.396	5.140	1	.023
12(BBB)	CS	-15.105	6.167	5.999	1	.014
13(BBB+)	CS	15.223	6.834	4.962	1	.026
14(A-)	LLRGL	-45.043	25.646	3.085	1	.079
	LLPTL	-126.210	78.281	2.599	1	.100
	CS	14.086	6.355	4.913	1	.027
15(A)	LLPTL	-168.728	72.485	5.419	1	.020
	LLPE	-41.196	18.391	5.018	1	.025
	LLRE	-2.438	10.468	6.378	1	.012

Table 4.9: Parameter estimates for the credit risk model with dummies (Model 2)

FSR	Variable	B	Std. Error	Wald	df	Sig.
6 (B)	LLRGL	86.907	19.852	19.165	1	.000
	SR	-3.251	1.508	4.648	1	.031
	T	2.820	.802	12.372	1	.000
7(B+)	LLRGL	54.571	15.021	13.198	1	.000
	CS	-25.726	13.259	3.765	1	.052
	SR	-1.270	.412	9.480	1	.002
	T	.801	.326	6.031	1	.014
	Size	-5.784	1.204	23.096	1	.000
8(BB-)	LLRGL	51.333	14.001	13.442	1	.000
	CS	-21.948	12.162	3.257	1	.071
	SR	-1.536	.383	16.047	1	.000
	T	1.183	.272	18.875	1	.000
9(BB)	LLRGL	62.957	13.628	21.341	1	.000
	CS	-15.035	11.173	1.811	1	.100
	SR	-1.472	.371	15.753	1	.000
	T	1.625	.244	44.261	1	.000
	Size	-8.258	1.103	56.102	1	.000
10(BB+)	LLRGL	51.735	13.456	14.783	1	.000
	SR	-1.486	.367	16.413	1	.000
	T	1.455	.224	42.057	1	.000
	Size	-8.561	1.056	65.750	1	.000
11(BBB-)	LLRGL	49.370	13.327	13.723	1	.000
	SR	-1.611	.365	19.489	1	.000
	T	1.114	.219	25.992	1	.000
	Size	-6.294	.989	40.471	1	.000
12(BBB)	LLRGL	27.173	13.235	4.215	1	.040
	SR	-1.383	.362	14.626	1	.000
	T	1.021	.210	23.652	1	.000

	Size	-6.275	.963	42.466	1	.000
13(BBB+)	SR	1.154	.366	9.957	1	.002
	T	1.084	.218	24.725	1	.000
	Size	6.090	.987	38.087	1	.000
14(A-)	LLRGL	-31.179	12.805	5.928	1	.015
	SR	.906	.362	6.275	1	.012
	T	.777	.205	14.420	1	.000
	Size	4.143	.940	19.432	1	.000
15(A)	SR	1.029	.358	8.273	1	.004
	T	.693	.201	11.881	1	.001
	Size	4.102	.927	19.598	1	.000

As presented in Tables 4.8 and 4.9, the reported significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant credit risk predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using credit risk predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile. That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

Table 4.8 shows that CS has a negative and statistically significant coefficient at the 1% level for BBB- ratings, at the 5% level for BBB ratings and at the 10% level for B^+ ratings. Also, CS has a positive and statistically significant coefficient at the 5% level for BBB+ and A- ratings. The negative sign associated with predictor estimates provides further evidence that low- and near-low-FSR banks in Middle East suffer from CS problems. In contrast, the positive sign associated with the predictor estimates confirms that high- and near-high-FSR banks maintain appropriate levels of capital buffers to absorb expected future credit risk exposures. Table 4.9 shows that CS has a negative and statistically significant coefficient at the 10% level for B+, BB- and BB ratings. In line with Model 1, the negative sign associated with the predictor estimates implies that low-FSR banks in Middle East are undercapitalised.

This finding provides a source of validity for the asset quality category as both categories are very close in terms of the nature of banking business.

Table 4.8 indicates that LLRGL has positive and statistically significant coefficients at the 1% level for B, BB-, BB+ and BBB- ratings and at the 5% level for BB ratings. In addition, LLRGL has negative and statistically significant coefficients at the 10% level for A- ratings. In line with Van-Roy (2006), the positive sign associated with predictor estimates implies that low-FSR banks have poor quality loan portfolios. In addition, this result provides a source of validity for the ILGL ratio result in the asset quality category. Also, this finding was confirmed by Poon and Firth’s (2005) conclusion that banks with high LLRGL ratios—while holding charge-off policy constant—will have poor quality loan portfolios and thus lower assigned FBRs.

However, the negative sign associated with the predictor estimates indicates that near-high-FSR banks have better quality loan portfolios. This is mainly because near-high-FSR banks are adopting firm management strategies and policies regarding issuance of corporate and retail loans. This argument is supported by the fact that average rate of LLRGL for low- and near-low-FSR banks (11.11%) is higher than the same average for high- and near-high-FSR banks (4.4%)[60](see appendix B and C, respectively). Similar to this, Table 4.9 shows that LLRGL has positive and statistically significant coefficients at the 1% level for B, B+, BB-, BB, BB+ and BBB- rating and at the 5% level for BBB ratings. On the other hand, LLRGL has a negative and statistically significant coefficient at the 5% level for A- ratings. This finding validates results reported for Model 1.

As shown in Table 4.8, LLRE has negative and statistically significant coefficients at the 5% level for A ratings. The negative sign associated with the predictor estimate implies that high-

[60] It is worth mentioning that the average rate of loan loss reserve to gross loans for low-FSR banks (14.27%) is higher than the same average for high-FSR banks (3.65%).

FSR banks are more conservative and rational regarding expected loan losses. This is done by building up a capital buffer against expected loan losses that are written off against banks. In line with banking activity, high-FSR banks are willing to maintain their good reputation and depositors' confidence level by reducing their probability of failure or bankruptcy by applying defensive or firm techniques to guide corporate and retail loans issuance. This argument is supported by the fact that average rate of LLRE for high-FSR banks (22.9%) is somewhat lower than the average rate of LLRE for low-FSR banks (62.3%).

As shown in Table 4.8, LLPTL has positive and statistically significant coefficients at the 1% level for BB^+ ratings, at the 5% level for BBB- ratings and at the 10% level for BB- ratings. In addition, LLPTL has negative and statistically significant coefficients at the 5% level for A ratings and at the 10% level for A- ratings. This finding is in accordance with results reported for the LLRGL ratio. The positive sign associated with the predictor estimates indicates that low-FSR banks employ poor credit-management techniques. Consequently, banks are forced to increase balances of annual provisions to alleviate expected future losses from poor quality loan portfolios.

However, the negative sign associated with the predictor estimates confirms that high- and near-high-FSR banks are more conservative in terms of loan issuance. It seems that high- and near-high-FSR banks are implementing firm credit-management techniques that result in better loan portfolio quality than low-FSR banks. Accordingly, high- and near-high-FSR banks estimate lower annual provisions than low-FSR banks. This argument is supported by the fact that the average rate of LLPTL for low- and near-low-FSR banks (1.47%) is higher than that for high- and near-high-FSR banks (0.73%) (see appendix B and C, respectively).

As observed in Table 4.8, LLPE has positive and statistically significant coefficients at the 5% level for BB+ and BBB- ratings and at the 10% level for BB- ratings. Moreover, LLPE has a negative and statistically significant coefficient at the 5% level for A ratings. In line with results reported for both LLPTL and LLRE, the positive sign associated with the predictor estimates validates that low-FSR banks are less conservative about their expected future loan losses. Accordingly, these banks do not accumulate appropriate amounts of capital cushion to lessen high credit risk exposure. This is mainly because low-FSR banks employ primitive credit-management techniques that ultimately result in poor credit decisions. This forces banks to anticipate higher provisions each year. However, the negative sign associated with the predictor estimate confirms an opposite scenario for high-FSR banks. This debate is confirmed by the fact that average rate of LLPE ratio for low-FSR banks (9.4%) is slightly higher than the average rate for high-FSR banks (8.35%).

Table 4.9 reveals that time effect (T) has positive and statistically significant coefficients at the 1% level for B, BB-, BB, BB+, BBB- , BBB, BBB+, A- and A ratings and at the 5% level for B+ ratings. This finding is compatible with results reported for the capital adequacy category.

Table 4.9 shows that SR has negative and statistically significant coefficients at the 1% level for B+, BB-, BB, BB+, BBB- and BBB ratings and at the 5% level for B ratings. Also, SR has a positive and statistically significant coefficient at the 1% level for BBB+ and A ratings and at the 5% level for A- ratings. This finding is similar to the results reported for both the asset quality and capital adequacy categories. The negative sign associated with the predictor estimates implies that low- and near-low-FSR banks are mainly located in countries that suffer from poor economic and financial conditions. However, the positive sign associated with the predictor estimates confirms that high- and near-high-FSR banks operate in countries with better economic and financial conditions.

As shown in Table 4.9, size has negative and statistically significant coefficients at the 1% level for B+, BB, BB+, BBB- and BBB ratings. Furthermore, size has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. This finding is comparable to results reported for both the asset quality and capital adequacy categories. The negative sign associated with the predictor estimates confirms that low- and near-low-FSR banks are small banks. On the contrary, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks are larger. This is mainly because large banks can diversify risk exposure more easily than small size banks because of economies of scale.

4.3.4 Liquidity models

Table 4.10: Liquidity results for ML models with and without bank FSR dummies [61]

Variables	Model 1 without dummies		Model 2 with dummies[62]	
	χ^2	*df*	χ^2	*df*
Intercept	63.01***	11	233.9***	11
CS	54.88***	11	48.06***	11
LADSTF	63.38***	11	50.69***	11
LR	73.14***	11	42.43***	11
Size			300.8***	11
SR			137.3***	11
T			91.98***	11
No. of observations	568		568	
χ^2	243.6***		815.0***	
Log Likelihood	0.002283***		0.001711***	
(Pseudo)[1] R^2	35.3%		77.1%	
Overall classification accuracy	27.5%		38.0%	

Note. Multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 and outliers are excluded. *, **, and *** denote statistically significant differences at the 10%, 5% and 1% levels, respectively.
[1]The researcher reports the value of Nagelkerke, which is an adjustment to Cox and Snell measure.

[61] The addition of IBR to the ML run increases the pseudo R^2 to 46.15%. However, unexpected singularities in the Hessian matrix were encountered. Therefore, the researcher excluded IBR from both models because of a large number of missing observations. The results are available from the researcher.
[62] SR and the country dummy variable are highly correlated at 73.4%. The researcher performed a regression run with the SR variable alone and pseudo R-square equals 77.1%. The researcher conducted another regression run with the country dummy variable alone and the pseudo R-square equals 72.0%. Thus, the researcher included the SR variable and dropped the country dummy variable for final the ML regression run for this category.

(1) Table 4.10 summarises the forward stepwise regression[63] results for Models 1 and 2 using the liquidity category. For Model 1, the results show that three statistically significant predictors—total equity to total assets ratio (CS), the ratio of liquid assets to deposits and short term funding ratio (LADSTF) and net loans to total assets ratio (LR)—are included in final model. For Model 2, the results show that six statistically significant predictors— CS, LADSTF, LR sovereign ratings (SR), time effect (T) and Size—are included in final model and are statistically significant at the 1% level.

(2) For Model 1, the statistical characteristic of model-fitting shows that final model is significant at the 1% level (χ^2 = 243.648, df = 33) and therefore outperforms the null. for Model 2, the statistical characteristic of model-fitting shows that final model is significant at the 1% level (χ^2 =814.974, df = 66) and as a result, outperforms the null.

(3) For Models 1 and 2, the goodness-of-fit shows that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This implies that the two models satisfactorily fit the data.

(4) For the explanatory power of Model 1 (pseudo R-square), the results show that three significant predictors account for 35.3% of FSR variation in the probability of moving from a current to subsequent bank FSR. For Model 2, the results show

[63] Note that the researcher ran the ML regression using the first and fourth quartile only for the liquidity category. The number of observations for Models 1 and 2 was 345. For Model 1, the results show that three statistically significant predictors (CS, LADSTF and LR) account for 42.4% of FSR variations. In line with this, the cross-classification matrix shows that the liquidity category classifies 38.8% of predicted FSR as correct and that it is relatively powerful in predicting A ratings with 84%. For Model 2, the results show that six statistically significant predictors (CS, LADSTF, LR, size, time and SR) account for 84.9% of FSR variations. The cross-classification matrix shows that the liquidity category with dummies classifies 54.8% of predicted FSRs correctly and that this model is relatively powerful in predicting B+, B and A ratings with 100%, 88.9% and 74.5%, respectively. Detailed results are available upon request.

that six significant predictors account for 77.1% of FSR variations in the probability of moving from a current to subsequent bank FSR.

(5) Regarding the classification power of liquidity for Model 1, the results show that this category classifies 27.5% of predicted FSRs correctly. Additionally, the cross-classification matrix shows that the liquidity category is relatively powerful in predicting BB- ratings, which corresponds to 63.6%. For Model 2, the results show that the liquidity category with dummies correctly classifies 38% of predicted FSRs. In addition, Model 2 is relatively powerful in predicting B and BB- ratings with 88.9% and 63.6%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant liquidity predictors that are associated with each bank rating individually. That is, Table 4.10 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant liquidity predictors that help increasing the probability of moving from a current to a higher FSR.

As revealed in Table 4.11, the results of the parameter estimates show that B, B+, BB- , BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings are most representative for Model 1 and the available data. The parameters of the final predictors—CS, LADSTF and LR—vary in their significance across different FSRs. As shown in Table 4.12, the results of the parameter estimates show that B, B+,BB-, BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings are most representative for Model 2 and the available data. The results show that parameters of the final predictors CS, LADSTF, LR, size, SR and time effect (T) vary in their significance across different ratings.

Table 4.11: Parameter estimates for the liquidity model without dummies (Model 1)

FSR	Variable	B	Std. Error	Wald	df	Sig.
6(B)	CS	-32.256	10.226	9.949	1	.002
	LR	12.009	4.651	6.667	1	.010
7(B+)	CS	-23.518	8.681	7.339	1	.007
8(BB-)	LADSTF	-17.196	3.517	23.900	1	.000
	CS	-22.246	8.183	7.390	1	.007
9(BB)	LADSTF	-5.468	2.213	6.105	1	.013
10(BB+)	LADSTF	-3.976	1.979	4.038	1	.044
11(BBB-)	LADSTF	-5.963	1.944	9.411	1	.002
12(BBB)	LADSTF	-6.196	1.870	10.976	1	.001
13(BBB+)	LADSTF	7.956	2.334	11.618	1	.001
	LR	-6.075	2.428	6.262	1	.012
14(A-)	LADSTF	7.782	2.002	15.103	1	.000
	LR	-4.595	1.977	5.403	1	.020
15(A)	LADSTF	3.184	1.867	2.907	1	.088
	LR	-3.047	1.771	2.961	1	.085
16(A+)	LR	-3.377	2.052	2.710	1	.100

Table 4.12: Parameter estimates for the liquidity model with dummies (Model 2)

FSR	Variable	B	Std. Error	Wald	df	Sig.
6(B)	CS	-45.510	15.749	8.350	1	.004
	LR	39.304	20.056	3.841	1	.050
	SR	-6.464	2.006	10.379	1	.001
	T	2.673	.625	18.319	1	.000
7(B+)	CS	-33.624	11.804	8.114	1	.004
	SR	-1.965	.504	15.168	1	.000
	T	1.140	.277	16.887	1	.000
	Size	-6.527	1.218	28.703	1	.000
8(BB-)	LADSTF	-12.343	3.680	11.252	1	.001
	CS	-27.795	12.299	5.108	1	.024
	SR	-2.221	.519	18.322	1	.000
	T	1.088	.294	13.667	1	.000
9(BB)	CS	-28.717	11.186	6.591	1	.010
	SR	-1.907	.492	15.051	1	.000
	T	1.357	.257	27.912	1	.000
	Size	-8.896	1.164	58.394	1	.000
10(BB+)	CS	-19.192	10.617	3.267	1	.071
	SR	-2.144	.486	19.476	1	.000
	T	1.292	.248	27.118	1	.000
	Size	-9.141	1.132	65.199	1	.000
11(BBB-)	LADSTF	-4.075	2.336	3.042	1	.081
	LR	6.651	3.805	3.055	1	.080
	SR	-2.252	.483	21.738	1	.000
	T	1.042	.244	18.211	1	.000
	Size	-6.706	1.059	40.116	1	.000
12(BBB)	LADSTF	-3.999	2.206	3.285	1	.070
	LR	10.197	3.675	7.699	1	.006
	SR	-2.171	.481	20.375	1	.000
	T	1.077	.240	20.167	1	.000
	Size	-6.484	1.040	38.861	1	.000
13(BBB+)	LADSTF	6.219	2.632	5.585	1	.018
	LR	-11.099	4.080	7.402	1	.007
	SR	1.891	.486	15.123	1	.000
	T	1.172	.247	22.554	1	.000
	Size	6.219	1.069	33.843	1	.000
14(A-)	LADSTF	6.907	2.027	11.606	1	.001

	LR	-10.304	3.606	8.165	1	.004
	SR	1.645	.480	11.760	1	.001
	T	.844	.236	12.790	1	.000
	Size	4.282	1.014	17.827	1	.000
15(A)	LR	-9.668	3.384	8.160	1	.004
	SR	1.761	.477	13.631	1	.000
	T	.831	.234	12.651	1	.000
	Size	4.232	1.005	17.718	1	.000
16(A+)	LR	-7.070	3.584	3.891	1	.049

As shown in tables 4.11 and 4.12, the reported significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant liquidity predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using liquidity predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile. That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

As seen in Table 4.11, CS has negative and statistically significant coefficients at the 1% level for B, B+ and BB- ratings. CS is statistically insignificant for high- and near-high-FSR banks in this category. The negative sign associated with the predictor estimates reflects the nature of the bank-rating system. As far as bank capitalisation is concerned, low-FSR banks are considered to be undercapitalised in comparison to high- and near-high-FSR banks. This finding complies with results reported under the asset quality category. Table 4.12 shows that CS has negative and statistically significant coefficients at the 1% level for B, B+ and BB ratings, at the 5% level for BB- ratings and at the 10% level for BB+ ratings. This finding verifies results reported for Model 1.

As shown in Table 4.11, LR has a positive and statistically significant coefficient at the 1% level for B ratings. In addition, the LR ratio has a negative and statistically significant coefficient at the 5% level for BBB+ and A- ratings and at the 10% level for A and A+ ratings. This finding confirms results reported by Belloti et al. (2011a), Chen (2012) and Öğüt et al. (2012), which indicate that banks with higher liquidity positions tend to obtain higher bank ratings. The positive sign associated with the predictor estimate for low-FSR banks is compatible with banking activity. Apparently, low-FSR banks are selling a larger number of poor quality loans that result in a higher degree of liquidity risk exposure. Subsequently, FSRs assigned by the CI rating agency are affected negatively. This finding validates asset quality category outcomes, which state that the average rate of ILGL for low- and near-low-FSR banks exceeds the average rate of ILGL for high- and near-high-FSR banks. Moreover, Poon et al. (2009) confirmed that banks with high loan-to-total asset ratios are assigned low FBRs. This is mainly because an increase in LR results in higher bank liquidity risk, which is the reason that a low-FSR is assigned.

Alternatively, the negative sign associated with the predictor estimates indicates that high- and near-high-FSR banks do not depend entirely on selling loans as their main source of revenue. However, they invest in other financial activities or instruments to maintain a safe liquidity position. It should be also noted that the average rate of LR for low- and near-low-FSR banks (54.7%) is higher than that for high- and near-high-FSR banks (43.5%) (see appendix B and C, respectively). In light of the global financial crisis of 2008, Basel III proposed new liquidity requirements to rectify liquidity positions within the banking industry. This explains why LR is relatively important for rating agencies in this region. Table 4.12 indicates that LR has a positive and statistically significant coefficient at the 1% level for BBB ratings; at the 5% level for B ratings and at the 10% level for BBB- ratings. In addition, LR has a negative and statistically significant coefficient at the 1% level for BBB+, A- and A ratings and at the 5% level for A+ ratings. This finding is in accordance with results reported for Model 1.

As shown in Table 4.11, LADSTF has a negative and statistically significant coefficient at the 1% level for BB-, BBB- and BBB ratings and at the 5% level for BB and BB+ ratings. Also, LADSTF has a positive and statistically significant coefficient at the 1% level for BBB+ and A- ratings and at the 10% level for A ratings. The positive sign associated with the predictor estimates suggests that high- and near-high-FSR banks invest more in liquid assets. High- and near-high-FSR banks tend to maintain good liquidity positions to withstand sudden withdrawals by customers and short-term funding. The findings are consistent with those of Poon and Firth (2005), Pasiouras et al. (2006), Godlewski (2007) and Chen (2012), who concluded that high-rated banks hold more liquid assets than low-rated bank.

It should be noted that high-FSR banks in the Middle East prefer excess liquidity. High liquidity is needed to fund growth in the retail market and to finance the booming small-medium size corporate sector (Corbett, 2009). In general, these two areas are considered huge opportunities for the potential growth of the banking industry in the Middle East region. Conversely, the negative sign associated with the predictor estimates indicates that low- and near-low-FSR banks do not maintain an appropriate level of liquid assets. Thus, banks are able neither to withstand sudden customer withdrawals nor to meet minimum liquidity requirement levels set by central banks. It also is worth mentioning that the average rate of LADSTF for high- and near-high-FSR banks (41.6%) is greater than the average rate for low- and near-low-FSR banks (33.1%) (see appendix C and B, respectively). As shown in Table 4.12, LADSTF has a negative and statistically significant coefficient at the 1% level for BB- ratings and at the 10% level for BBB- and BBB ratings. Moreover, LADSTF has a positive and statistically significant coefficient at the 1% level for A- ratings and at the 5% level for BBB+ ratings. Concisely, this finding is in agreement with results reported for Model 1.

Table 4.12 shows that SR has negative and statistically significant coefficients at the 1% level for B, B+, BB-, BB, BB+, BBB- and BBB ratings. In addition, SR has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. This finding is compatible with results reported for asset quality, capital adequacy and credit risk categories.

As indicated in Table 4.12, time effect (T) has positive and statistically significant coefficients at the 1% level for B, B+, BB-, BB, BB+, BBB-, BBB, BBB+, A- and A ratings. The positive sign associated with the predictor estimates confirms that bank FSRs in the Middle East region slightly improved during period from 2001 to 2009. This result is consistent with results reported for both credit risk and capital adequacy categories.

Table 4.12 shows that size has negative and statistically significant coefficients at the 1% level for B+, BB, BB+, BBB- and BBB ratings. Moreover, size has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. This finding is similar to results reported for the asset quality, capital adequacy and credit risk categories.

4.3.5 Profitability models

Table 4.13: Profitability results for the ML model with and without bank FSR dummies [64]

Variables	Model 1 without Dummies		Model 2 with Dummies[65]	
	χ^2	*df*	χ^2	*df*
Intercept	60.88***	11	108.9***	11
CS	86.13***	11	38.59***	11
CIR	79.33***	11	38.95***	11
TME	80.70***	11	73.25***	11
NIM	20.93**	11	33.63***	11
AU	86.13***	11	87.62***	11
REP	24.69***	11	53.26***	11
R0AE	25.72***	11	21.89**	11
ECE			16.50*	11
Size			270.3***	11
SR			73.46***	11
No. of observations	491		491	
χ^2	588.7***		969.7***	
Log Likelihood	0.001603***		0.001222***	
(Pseudo)[1] R^2	70.7%		87.1%	
Overall classification accuracy	38.5%		49.5%	

Note. The multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 and outliers are excluded. *, **, and *** denote statistically significant differences at the 10%, 5% and 1% level, respectively.
[1]The researcher reports the value of Nagelkerke, which is an adjustment to Cox and Snell measure.

(1) Table 4.13 reports forward stepwise regression[66] results for Models 1 and 2 for the profitability category. For Model 1, the results show that seven predictors are

[64] PTOIAA, NOITAA, DPO, INODAE, NOINI are excluded from the two models because of a large number of missing observations.
[65] SR and country dummy variables are highly correlated at 73.4%. The researcher performed a regression run with the SR variable alone, and pseudo R-square equals 87.1%. The researcher conducted another regression run with the country dummy variable alone, and pseudo R-square equals 75.7%. Thus, the researcher included the SR variable and dropped the country dummy variable for the final ML regression run for this category.
[66] The researcher ran the ML regression using first and fourth quartiles only for the profitability category. The number of observations for Models 1 and 2 were 302. For Model 1, the result shows that five statistically significant predictors (CS, CIR, TME, NIM and AU) account for 77.3% of FSR variations. In addition, the cross-classification matrix shows that profitability category classifies 54.3% of predicted FSRs correctly and that it is relatively powerful in predicting B, A, B+ and BBB^- ratings that correspond to 100%, 77%, 75% and 65.6%, respectively. For Model 2, the result shows that nine statistically significant predictors (CS, CIR, TME, AU, REP, OER, size, time and SR) accounted for 92% of FSR variations. The cross-classification matrix shows

included in the final model. Six predictors—ratio of total equity to total assets (CS), the ratio of cost to income ratio (CIR), the ratio of tax management efficiency (TME), asset utilisation (AU), recurring earning power (REP) and return on average equity (ROAE)—are statistically significant at the 1% level. One predictor, the ratio of net interest margin (NIM), is statistically significant at the 5% level. For Model 2, the results show that 10 significant predictors are included in the final model. Eight predictors, CS, CIR, TME, NIM, AU, REP, SR and Size effect, are statistically significant at the 1% level. One predictor, ROAE, is significant at the 5% level. One predictor, expense control efficiency (ECE), is significant at the 10% level.

(2) For Model 1, the statistical characteristic of model fitting confirms that the final model is significant at the 1% level (χ^2 = 588.719; df = 77) and accordingly outperforms the null. For Model 2, the statistical characteristic of model-fitting shows that the final model is significant at the 1% level (χ^2 = 969.713; df = 110) and thus outperforms the null.

(3) For Models 1 and 2, the goodness-of-fit shows that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This indicates that the two models acceptably fit the data.

(4) Regarding the explanatory power of the Model 1 (pseudo R-square), the results show that seven significant predictors account for 70.7% of FSR variations in the probability of moving from a current to subsequent bank FSR. For Model 2, the results show that 10 significant predictors account for 87.1% of FSR variations in the probability of moving from a current to subsequent bank FSR.

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that the profitability category with dummies classifies 68.9% of predicted FSR as correct and that this model is relatively powerful in predicting B, B+ and A ratings that correspond to 100%, 100% and 83.9%, respectively. Detailed results are available from the researcher.

(5) Concerning the classification power of profitability for Model 1, the results show that this category classifies 38.5% of predicted FSRs correctly. Additionally, the cross-classification matrix shows that profitability category is relatively powerful in predicting B, B+ and A ratings that correspond to 100%, 87.5% and 67.8%, respectively. For Model 2, the results show that the profitability category with dummies classifies 49.5% of the predicted FSRs as correct. In addition, Model 2 is relatively powerful in predicting B, B+, A+, BB- and A ratings which corresponds to 100%, 100%, 69.4%, 66.7% and 63.2%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant profitability predictors that are associated with each bank rating individually. That is, Table 4.13 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant profitability predictors that help increasing the probability of moving from a current to a higher FSR.

Table 4.14 shows that the parameters estimates of B+, BB-, BB, BB+, BBB-, BBB, BBB+, A- and A ratings are most representative for Model 1 and the available data. The parameters of the final predictors CS, CIR, TME, NIM, AU, REP and ROAE vary in their significance across different FSRs. Table 4.15 reports that the parameters estimates of B+, BB-, BB, BB+, BBB-, BBB, BBB+, A- and A ratings are most representative for Model 2 and the available data. The parameters of the final predictors CS, CIR, TME, NIM, AU, REP, ROAE, ECE, size and SR vary in significance across bank FSRs.

Table 4.14: Parameter estimates for the profitability model without dummies (Model 1)

FSR	Variable	B	Std. Error	Wald	df	Sig.
7(B+)	AU	-495.034	139.891	12.522	1	.000
	CIR	21.856	5.162	17.926	1	.000
	CS	-47.856	23.437	4.169	1	.041
	NIM	-225.934	84.533	7.144	1	.008
	ROAE	-16.887	6.151	7.538	1	.006
	REP	-247.804	146.429	2.864	1	.091
	TME	-16.183	6.289	6.621	1	.010
8(BB-)	CIR	20.195	4.834	17.456	1	.000
	ROAE	-9.318	5.411	2.965	1	.085
	REP	-135.360	103.419	2.913	1	.081
	TME	-14.991	6.225	5.799	1	.016
9(BB)	AU	-187.119	41.507	20.323	1	.000
	CIR	10.891	5.286	4.245	1	.039
	NIM	-126.597	55.420	5.218	1	.022
	TME	-13.786	6.418	4.614	1	.032
10(BB+)	AU	-147.927	35.597	17.269	1	.000
	CIR	19.481	4.737	16.916	1	.000
	CS	-20.684	10.376	3.974	1	.046
	NIM	-126.407	51.124	6.114	1	.013
11(BBB-)	AU	-116.132	35.108	10.942	1	.001
	CIR	19.448	4.744	16.806	1	.000
	CS	-35.710	10.256	12.123	1	.000
	NIM	-141.854	51.322	7.640	1	.006
	ROAE	-9.853	4.322	5.199	1	.023
	TME	-12.426	6.233	3.974	1	.046
12(BBB)	AU	-88.737	33.562	6.990	1	.008
	CIR	15.287	4.710	10.535	1	.001
	CS	-27.488	9.959	7.618	1	.006
	NIM	-119.944	50.112	5.729	1	.017
	TME	-14.170	6.198	5.227	1	.022
13(BBB+)	AU	99.648	36.870	7.305	1	.007
	CIR	-15.965	5.060	9.954	1	.002
	NIM	101.005	51.636	3.826	1	.050
	ROAE	10.101	4.284	5.559	1	.018
14(A-)	NIM	141.439	51.019	7.686	1	.006
	ROAE	10.084	4.221	5.707	1	.017
15(A)	AU	55.909	32.366	2.984	1	.084
	NIM	112.051	50.198	4.983	1	.026
	ROAE	8.421	4.189	4.041	1	.044

Table 4.15: Parameter estimates for the profitability model with dummies (Model 2)

FSR	Variable	B	Std. Error	Wald	df	Sig.
7(B+)	AU	-765.356	417.550	3.360	1	.067
	CIR	21.053	9.519	4.892	1	.027
	NIM	-473.137	178.661	7.013	1	.008
	TME	-21.449	12.432	2.977	1	.084
8(BB-)	AU	-435.700	207.229	4.421	1	.036
	CIR	67.597	21.304	10.068	1	.002
	REP	-892.693	313.924	8.086	1	.004
	SR	-3.123	.917	11.602	1	.001
9(BB)	ECE	-18.395	8.133	5.116	1	.024
	AU	-234.608	67.668	12.020	1	.001
	NIM	-354.180	85.320	17.233	1	.000
	ROAE	-22.250	13.295	2.801	1	.094
	Size	-10.583	1.498	49.901	1	.000
	SR	-.601	.370	2.639	1	.100
10(BB+)	ECE	-23.862	7.638	9.761	1	.002
	AU	-154.717	62.421	6.143	1	.013
	CIR	13.768	7.719	3.181	1	.074
	CS	-42.994	23.603	3.318	1	.069
	NIM	-315.296	79.111	15.884	1	.000
	Size	-9.879	1.369	52.104	1	.000
	SR	-1.086	.365	8.865	1	.003
11(BBB-)	ECE	-22.603	7.563	8.933	1	.003
	AU	-113.826	61.262	3.452	1	.063
	CIR	13.892	7.710	3.247	1	.072
	CS	-56.538	23.063	6.010	1	.014
	NIM	-305.404	77.971	15.342	1	.000
	Size	-7.907	1.300	36.994	1	.000
	SR	-.934	.359	6.771	1	.009
12(BBB)	ECE	-21.308	7.428	8.229	1	.004
	CS	-45.397	23.120	3.855	1	.050
	NIM	-292.212	76.830	14.466	1	.000
	ROAE	-22.418	13.084	2.936	1	.087
	Size	-7.669	1.286	35.578	1	.000
	SR	-.712	.356	4.009	1	.045
13(BBB+)	ECE	23.697	7.670	9.545	1	.002
	CIR	-13.518	7.753	3.040	1	.081
	NIM	255.951	76.447	11.210	1	.001
	Size	6.795	1.299	27.346	1	.000
14(A-)	ECE	19.726	7.009	7.921	1	.005
	NIM	253.244	75.829	11.154	1	.001
	TME	8.265	10.464	5.799	1	.030
	Size	5.094	1.233	17.058	1	.000
15(A)	ECE	16.786	6.644	6.384	1	.012
	NIM	204.107	72.905	7.838	1	.005
	TME	8.610	10.658	6.621	1	.019
	Size	4.331	1.210	12.824	1	.000
	SR	.647	.346	3.506	1	.061

As shown in Tables 4.14 and 4.15, the reported significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant profitability predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using profitability predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile. That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

As can be seen in Table 4.14, CS has negative and statistically significant coefficients at the 1% level for BBB- and BBB ratings and at the 5% level for B+ and BB+ ratings. CS is statistically insignificant for high- and near-high-FSR banks in this category. This finding is in accordance with results reported earlier for the asset quality and liquidity categories. The negative sign associated with predictor estimates indicates that low- and near-low-FSR banks in the Middle East are not accumulating an appropriate amount of capital buffer to compensate high risk weighted assets. In line with this, Table 4.15 reports that CS has a negative and statistically significant coefficient at the 5% level for BBB- and BBB ratings and at the 10% level for BB+ ratings.

As shown in Table 4.14, the TME ratio has a negative and statistically significant coefficient at 1% level for B+ ratings and at the 5% level for BB-, BB, BBB- and BBB ratings. The negative sign associated with the predictor estimates indicates that low- and near-low-FSR banks are incapable of using security gains or losses and other tax-management tools (such as the purchase of tax-exempt bonds) to minimise banks’ tax exposure. Table 4.15 reveals that the TME ratio has a negative and statistically significant coefficient at the 10% level for B+ ratings. In addition, TME has a positive and statistically significant coefficient at the 5% level for A- and A ratings. The positive sign associated with the predictor estimates confirms that high- and near-high-FSR banks are proficient and experienced in terms of using new financial instruments or techniques to reduce banks tax exposure. This argument is supported by the fact that average rate of TME for low- and near-low-FSR banks (80.5%) is somewhat lower than the average rate for high- and near-high-FSR banks (97.1%) (see appendix B and C, respectively).

Table 4.14 shows that CIR has a positive and statistically significant coefficient at the 1% level for B+, BB-, BB+, BBB- and BBB ratings and at the 5% level for BB ratings. In addition, CIR has a negative and statistically significant coefficient at the 1% level for BBB+ ratings. This ratio provides insight into bank management quality as well as operating cost variations. The positive sign associated with the predictor estimates implies that low- and near-low-FSR banks are managing cost-side activities inefficiently relative to the generated-income side. On the other hand, the negative sign associated with the predictor estimate shows that near-high-FSR banks are operating at low cost.

This result is along the lines of Pasiouras et al. (2006) and Van-Roy (2006), who concluded that banks with fairly low cost-to-income ratios are assigned high ratings. This finding also is consistent with the new era of banking industry, which focuses on movement toward automation and installation of sophisticated electronic systems instead of older, labour-based production and delivery systems. This brings about the reduction in bank overhead costs relative to generated income. In line with this, Poon et al. (1999) stated that profitability is positively associated with high ratings in the case of Moody's BFSRs. It is worth mentioning that the average rate of CIR for low- and near-low-FSR banks (46.5%) is higher than the average rate for high- and near-high-FSR banks (34.6%) (see appendix B and C, respectively). Table 4.15 reports that CIR has a positive and statistically significant coefficient at the 1% level for BB- ratings, at the 5% level for B+ ratings and at the 10% level for BB+ and BBB- ratings. Furthermore, CIR has a negative and statistically significant coefficient at the 10% level for BBB+ ratings. This finding is compatible with results reported for Model 1.

As can be seen in Table 4.14, AU has a negative and statistically significant coefficient at the 1% level for B+, BB, BB+, BBB- and BBB ratings. In addition, AU has a positive and statistically significant coefficient at the 1% level for BBB+ ratings and at the 10% level for A ratings. The negative sign associated with the predictor estimates indicates that low- and near-low-FSR banks do not efficiently utilise their available assets (i.e., loans, investment securities and fees earned from fiduciary activities) to generate an appropriate amount of total operating revenue (interest and non-interest). On the contrary, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks are implementing effective asset portfolio management policies. It should be noted that average rate of AU for low- and near-low-FSR banks (6.2%) is slightly lower than average rate for high- and near-high-FSR banks (7.3%) (see appendix B and C, respectively). Table 4.15 reveals that AU has a negative and statistically significant coefficient at the 1% level for BB ratings, at the 5% level for BB- and BB+ ratings and at the 10% level for B+ and BBB- ratings. This finding confirms results reported for Model 1.

As shown in Table 4.14, NIM has a negative and statistically significant coefficient at the 1% level for B+ and BBB- ratings and at the 5% level for BB, BB+ and BBB ratings. In addition, the NIM ratio is associated with a positive and statistically significant coefficient at the 1% level for A- and at the 5% level for BBB+ and A ratings. The negative sign associated with predictor estimates denotes that low- and near-low-FSR banks in the Middle East make unprofitable operating decisions, which means that banks pay interest expenses that are considerably higher than returns generated by bank investments. In other words, low- and near-low-FSR banks are incapable of increasing the spread between interest revenue generated by earning assets and interest expense paid on interest-bearing liabilities.

On the other hand, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks are proficient and qualified in generating the maximum amount of revenue by using the cheapest sources of funding. This is confirmed by Godlewski (2007), who stated that profitable banks are associated with lower bank default probability and thus higher bank ratings. Additionally, this argument is supported by the fact that the average rate of NIM for high- and near-high-FSR banks (3.2%) is slightly higher than the average rate for low- and near-low-FSR banks (3.0%) (see appendix C and B, respectively). Furthermore, this finding is in line with results reported for CIR ratio. Finally, these results provide clear evidence that bank profitability is a strong determinant of bank ratings (Pasiouras et al., 2006; Poon et al., 1999; Poon and Firth, 2005; Van-Roy, 2006). It can be also observed in Table 4.15 that NIM has a negative and statistically significant coefficient at the 1% level for B+, BB, BB+, BBB-, BBB ratings. In addition, NIM has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. This finding is in agreement with results reported for Model 1.

Table 4.14 indicates that ROAE has a negative and statistically significant coefficient at the 1% level for B+ ratings, at the 5% level for BBB- ratings and at the 10% level for BB- ratings. In addition, ROAE has a positive and statistically significant coefficient at the 5% level for BBB+, A- and A ratings. This finding is in line with results reported by Belloti et al. (2011a) and Öğüt et al. (2012). It is worth noting that this ratio must be carefully analysed as it neglects overleveraged banks. The negative sign associated with the predictor estimates indicates that low-FSR banks either suffer from expense-control problems or a decline in revenues. This definitely erodes net income, which negatively affects the rate of return earned on funds invested by stockholders of low-FSR banks.

In contrast, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks employ efficient banking operation techniques and strategies that result in superior shareholder returns. This debate is confirmed by the fact that average rate of ROAE for low- and near-low-FSR banks (15.4%) is relatively lower than the average rate for high- and near-high-FSR banks (17.8%) (see appendix B and C, respectively). Whereas Table 4.15 reveals that ROAE has a negative and statistically significant coefficient at the 10% level for BB and BBB ratings. The negative sign associated with the predictor estimates is similar to results reported for Model 1.

It can be observed from Table 4.14 that REP has a negative and statistically significant coefficient at the 10% level for B+ and BB- ratings. The negative sign associated with the predictor estimates denotes that low-FSR banks unable to use their assets to generate an appropriate amount of income even after adding back the provision for loan losses. This finding is in harmony with results reported by Poon et al. (1999) Poon and Firth (2005), Pasiouras et al. (2006) and Van-Roy (2006). Consequently, Table 4.15 shows that REP has a negative and statistically significant coefficient at the 1% level for BB- ratings. This finding is compatible with results reported for Model 1.

As seen in Table 4.15, ECE has a negative and statistically significant coefficient at the 1% level for BB+, BBB- and BBB ratings and at the 5% level for BB ratings. Also, ECE has a positive and statistically significant coefficient at the 1% level for BBB+ and A- ratings and at the 5% level for A ratings. The negative sign associated with the predictor estimates implies that low- and near-low-FSR banks are incapable to control operating expenses efficiently.

On the contrary, the positive sign associated with the predictor estimates denotes that high- and near-high-FSR banks have better control over their operating expenses. This is mainly because high- and near-high-FSR banks are more enthusiastic about advances in automation and mergers. Accordingly, this brings about the elimination of many overlapping facilities and thus reduces overhead and operating expenses. It is also worth mentioning that the average rate of ECE for high- and near-high-FSR banks (34.5%) is slightly higher than the average rate for low- and near-low-FSR banks (27%) (see appendix C and B, respectively).

Table 4.15 reveals that SR has negative and statistically significant coefficients at the 1% level for BB-, BB+ and BBB- ratings, at the 5% level for BBB ratings and at the 10% level for BB ratings. Correspondingly, SR has a positive and statistically significant coefficient at the 10% level for A ratings. The negative sign associated with the predictor estimates provides further evidence that banks located in countries with low SRs are assigned low- and near-low FSRs. On the contrary, the positive sign associated with the predictor estimate confirms that banks located in countries with better macroeconomic and institutional indicators are assigned high- and near-high FSRs. This finding is consistent with results reported for Model 2 for the asset quality, capital adequacy, credit risk and liquidity categories.

As shown in Table 4.15, size has negative and statistically significant coefficients at the 1% level for BB, BB+, BBB- and BBB ratings. Moreover, size has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. The negative sign associated with the predictor estimates implies that small banks are assigned low- and near-low FSRs. This may be a result of the higher probability of failure or the lesser ability to diversify small banks' operations. On the contrary, the positive sign associated with the predictor estimates signifies that large banks are assigned high- and near-high FSRs. Apparently, large banks benefit from economies of scale. This finding is in agreement with results reported for Model 2 for asset quality, capital adequacy, credit risk and liquidity categories.

4.3.6 All financial category models

Table 4.16: Results for all financial categories for the ML model with and without bank FSR dummies

Variables	Model 1 without dummies		Model 2 with dummies	
	χ^2	*df*	χ^2	*df*
Intercept	23.75***	10	27.56***	10
CS	46.10***	10	111.9***	10
LLRGL	102.8***	10	108.8***	10
TME	398.1***	10	48.82***	10
ECE	30.48***	10	60.47***	10
TCR	39.09***	10	51.75***	10
AU	44.73***	10	58.82***	10
EM	28.09***	10	32.05***	10
CIR	34.45***	10	27.63***	10
LR	41.63***	10	32.89***	10
LLPTL	23.09***	10	27.09***	10
LLRIL	46.30***	10	40.90***	10
NIEAA	17.41*	10		
SR			62.09***	10
No. of observations	419		419	
χ^2	823.4***		868.0***	
Log Likelihood	0.00997***		0.00952***	
(Pseudo)[1] R^2	87.1%		88.6%	
Overall classification accuracy	53.5%		56.1%	

The multicollinearity is addressed by examining the correlation matrix and VIF scores. The predictors associated with VIF > 5 and outliers are excluded. *, **, and *** denote statistically significant differences at the 10%, 5% and 1% levels, respectively.
[1]The researcher reports the value of Nagelkerke, which is an adjustment to the Cox and Snell measure.

(1) Table 4.16 presents forward stepwise regression[67] results for Models 1 and 2 for all financial categories. For Model 1, the results show that 12 statistically

[67] The researcher ran the ML regression using first and fourth quartile data only for all financial categories. The number of observations for Models 1 and 2 were 246. For Model 1, the result shows that nine statistically significant predictors (CS, LLPTL, ILGL, TME, LADSTF, AU, REP, TCR and EM) account for 88.1% of FSR variations. In addition, the cross-classification matrix shows that all financial categories without dummies model (model 1) classify 63.4% of predicted FSR as correct and that it is relatively powerful in predicting B, BB-, A and BBB- ratings that correspond to 100%, 100%, 86.4% and 73.5% , respectively. For Model 2, the result shows that 10 statistically significant predictors (CS, AU, TCR, TME, LLRIL, ENL, LLPNIR, SR, time and size) account for 94.7% of FSR variations. The cross-classification matrix shows that all financial categories with dummies model (model 2) classify 76% of predicted FSRs as correct. In addition, this model is relatively powerful in predicting B, BB+, BB- , BBB-, BB- and A ratings that corresponds to 100%, 88.2%, 85.7%, 85.7% and 84%, respectively. Detailed results are available from the researcher.

significant predictors are included in final model. Eleven predictors—total equity to total assets (CS), loan loss reserve to gross loans (LLRGL), tax-management efficiency (TME), expense-control efficiency (ECE), total capital ratio (TCR), asset utilisation (AU), equity multiplier (EM), cost-to-income ratio (CIR), loan ratio (LR), loan loss provision to total loans (LLPTL) and loan loss reserve to impaired loans (LLRIL)—are statistically significant at the 1% level. One predictor—non-interest expense to average assets (NIEAA)—is statistically significant at the 10% level. For Model 2, the results indicate that 12 statistically significant predictors are included in final model. These predictors—CS, LLRGL, TME, ECE, TCR, AU, EM, CIR, LR, LLPTL, LLRIL and SR—are statistically significant at the 1% level.

(2) For Model 1, the statistical characteristic of model-fitting shows that the final model is significant at the 1% level ($\chi^2 = 823.357$; df = 120) and thus outperforms the null. For Model 2, the statistical characteristic of model-fitting shows that the final model is significant at the 1% level ($\chi^2 = 868.036$; df = 120) and accordingly outperforms the null.

(3) For Models 1 and 2, the models' goodness-of-fit shows that the significance of the two tests (Pearson and deviance) are greater than 0.05 (1.00). This means that the two models adequately fit the data.

(4) Regarding the explanatory power of Model 1 (pseudo R-square), the results show that 12 significant predictors account for 87.1% of FSR variations in the probability of moving from a current to subsequent bank FSR. For Model 2, the results show that 12 significant predictors account for 88.6% of FSR variations in the probability of moving from a current to subsequent bank FSR.

(5) Regarding the classification power of all financial categories for Model 1, the results show that this model classifies 53.5% of predicted FSRs as correct. Moreover, the cross-classification matrix shows that Model 1 is comparatively powerful in predicting B, BB-, BB+ and A ratings, which corresponds to 100%, 100%, 67.6% and 65.4%, respectively. In line with Model 1, Model 2 results show that all financial ratios including dummies classify 56.1% of predicted FSRs as correct. In addition, Model 2 is fairly powerful in predicting B, BB-, BBB and BB+ ratings, which corresponds to 100%, 100%, 69.5% and 64.7%, respectively.

The estimation algorithm of Multinomial Logit offers an advantage of examining the significant all financial predictors that are associated with each bank rating individually. That is, Table 4.16 does not show the trend and the magnitude of each predictor coefficient across bank FSRs. It is important for bank managers to find out and focus on the significant financial predictors that help increasing the probability of moving from a current to a higher FSR.

As can be seen in Table 4.17, the parameter estimates for BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings are most representative for Model 1 and available data. The parameters of the final predictors CS, LLRGL, TME, ECE, TCR, AU, EM, CIR, LR, LLPTL, LLRIL and NIEAA vary in their significance across different FSRs. Table 4.18 indicates that the parameter estimates for BB, BB+, BBB- , BBB, BBB+, A-, A and A+ ratings are most representative for Model 2 and the available data. The parameters of final predictors CS, LLRGL, TME, ECE, TCR, AU, EM, CIR, LR, LLPTL, LLRIL and SR vary in their significance across different FSRs.

Table 4.17: Parameter estimates for all financial categories' model without dummies (Model 1)

FSR	Variable	B	Std. Error	Wald	df	Sig.
9 (BB)	LLRGL	96.815	22.369	18.733	1	.000
	AU	-171.044	52.048	10.800	1	.001
	CIR	22.403	7.623	8.636	1	.003
	NIEAA	276.978	133.730	4.290	1	.038
	EM	1.433	.365	15.426	1	.000
	CS	-81.607	21.604	14.269	1	.000
	LLRIL	-6.174	2.102	8.626	1	.003
	TCR	-29.406	13.144	5.005	1	.025
	TME	-20.178	7.092	8.095	1	.004
	LR	20.624	5.720	12.999	1	.000
10(BB+)	LLRGL	88.932	22.232	16.001	1	.000
	ECE	-17.752	6.030	8.667	1	.003
	AU	-218.326	47.184	21.410	1	.000
	CIR	17.120	8.253	4.303	1	.038
	EM	1.290	.345	14.002	1	.000
	CS	-85.279	20.589	17.157	1	.000
	LLRIL	-6.124	1.362	20.213	1	.000
	TME	-12.427	7.443	2.787	1	.095
	LLPTL	199.379	122.091	2.667	1	.100
11(BBB-)	LLRGL	91.303	21.903	17.376	1	.000
	ECE	-13.340	4.188	10.146	1	.001
	AU	-155.507	41.086	14.326	1	.000
	CIR	18.488	6.913	7.153	1	.007
	EM	1.818	.398	20.913	1	.000
	CS	-132.167	23.864	30.674	1	.000
	LLRIL	-1.477	.728	4.124	1	.042
	TCR	-20.472	12.116	2.855	1	.091
	TME	-18.302	6.856	7.126	1	.008
	LR	11.201	4.772	5.510	1	.019
12(BBB)	LLRGL	68.531	21.730	9.946	1	.002
	ECE	-7.719	3.776	4.178	1	.041
	AU	-128.461	38.771	10.978	1	.001
	CIR	15.362	6.243	6.055	1	.014
	EM	1.876	.398	22.190	1	.000
	CS	-112.659	23.106	23.773	1	.000
	LLRIL	-2.431	.619	15.410	1	.000
	TCR	-33.191	11.618	8.162	1	.004
	TME	-18.158	6.782	7.167	1	.007
	LR	16.691	4.453	14.049	1	.000
13(BBB+)	LLRGL	-39.201	23.464	2.791	1	.095
	ECE	13.361	4.166	10.286	1	.001
	AU	133.465	40.091	11.083	1	.001
	EM	1.751	.417	17.666	1	.000
	CS	103.883	24.282	18.303	1	.000
	LLRIL	.964	.546	3.116	1	.078
	TCR	32.306	12.101	7.127	1	.008
	TME	13.108	6.843	3.669	1	.055
	LR	-14.898	4.625	10.374	1	.001
14(A-)	LLRGL	-62.357	21.294	8.575	1	.003
	ECE	15.672	3.906	16.101	1	.000
	EM	1.570	.440	12.719	1	.000
	CS	99.657	24.658	16.334	1	.000
	LLRIL	.708	.436	2.641	1	.100

	TCR	20.557	11.356	3.277	1	.070
	LR	-10.383	4.290	5.858	1	.016
15(A)	ECE	-9.587	3.737	6.581	1	.010
	EM	1.815	.399	20.749	1	.000
	CS	82.780	23.108	12.833	1	.000
	TCR	35.752	10.919	10.720	1	.001
	LR	-12.684	4.140	9.388	1	.002
16(A+)	EM	1.745	.550	10.069	1	.002
	CS	60.483	33.324	3.294	1	.070
	TCR	29.639	11.460	6.689	1	.010
	LR	-11.035	4.601	5.752	1	.016

Table 4.18: Parameter estimates for all financial categories' model with dummies (Model 2)

FSR	Variable	B	Std. Error	Wald	df	Sig.
9(BB)	AU	-149.516	40.880	13.377	1	.000
	LLPTL	127.493	75.867	2.824	1	.093
	TCR	-24.800	15.015	2.728	1	.099
	LLRIL	-6.468	2.357	7.529	1	.006
	CS	-108.565	27.741	15.316	1	.000
	EM	1.699	.434	15.325	1	.000
	LLRGL	100.356	26.518	14.322	1	.000
	CIR	12.004	6.088	3.887	1	.049
	LR	12.879	7.323	3.093	1	.079
10(BB+)	SR	-1.264	.438	8.340	1	.004
	ECE	-20.493	6.187	10.971	1	.001
	AU	-194.027	38.314	25.645	1	.000
	LLPTL	259.671	88.060	8.695	1	.003
	LLRIL	-5.862	1.470	15.912	1	.000
	CS	-121.947	27.092	20.262	1	.000
	EM	1.503	.416	13.066	1	.000
	LLRGL	98.376	26.338	13.952	1	.000
	CIR	9.822	6.051	2.635	1	.100
	LR	14.090	6.634	4.510	1	.034
11(BBB-)	SR	-1.747	.418	17.457	1	.000
	ECE	-13.990	4.451	9.879	1	.002
	AU	-114.580	35.335	10.515	1	.001
	LLPTL	130.131	74.688	3.036	1	.081
	CS	-172.460	29.070	35.195	1	.000
	EM	2.048	.447	20.977	1	.000
	LLRGL	103.496	26.171	15.639	1	.000
	CIR	9.984	5.225	3.652	1	.056
	LR	22.684	5.883	14.867	1	.000
12(BBB)	SR	-1.237	.395	9.797	1	.002
	ECE	-11.250	3.899	8.326	1	.004
	AU	-98.684	31.660	9.716	1	.002
	LLPTL	138.669	74.001	3.511	1	.061
	TCR	-26.943	13.648	3.897	1	.048
	LLRIL	-2.140	.643	11.093	1	.001
	CS	-139.804	28.108	24.738	1	.000
	EM	2.043	.447	20.919	1	.000
	LLRGL	75.979	25.901	8.605	1	.003
	LR	22.295	5.536	16.221	1	.000
13(BBB+)	SR	.978	.396	6.088	1	.014
	ECE	16.541	4.186	15.618	1	.000
	AU	117.914	32.306	13.322	1	.000

	TCR	27.361	14.095	3.768	1	.052
	LLRIL	.940	.571	2.708	1	.100
	CS	124.727	29.556	17.809	1	.000
	EM	1.874	.476	15.483	1	.000
	LLRGL	-46.658	27.345	2.911	1	.088
	LR	-19.001	5.649	11.314	1	.001
14(A-)	SR	1.091	.390	7.842	1	.005
	ECE	17.899	3.923	20.818	1	.000
	LLPTL	-135.646	72.590	3.492	1	.062
	CS	126.343	29.128	18.814	1	.000
	EM	1.743	.479	13.221	1	.000
	LLRGL	-70.906	25.551	7.701	1	.006
	LR	-17.714	5.349	10.968	1	.001
15(A)	SR	1.320	.382	11.924	1	.001
	ECE	-13.337	3.813	12.235	1	.000
	TME	20.538	10.943	3.522	1	.061
	TCR	28.233	13.062	4.672	1	.031
	CS	112.103	27.962	16.073	1	.000
	EM	1.984	.447	19.693	1	.000
	LR	-20.234	5.249	14.862	1	.000
16(A+)	TME	43.130	18.514	5.427	1	.020
	TCR	35.110	13.878	6.400	1	.011
	EM	1.712	.607	7.963	1	.005
	LLRGL	-47.169	26.310	3.214	1	.073
	LR	-13.160	5.432	5.869	1	.015

As shown in tables 4.17 and 4.18, the reported significant predictors are not determinants of every bank FSR. The forward stepwise algorithm helps show the significant financial predictor(s) for each FSR individually. Moreover, the trend (either positive or negative) of each predictor may vary across FSRs. This result carries important implications to bank managers when planning for improving bank FSRs using all financial and non-financial predictors. That is, bank FSR may require an increase (or decrease) in a certain predictor. In terms of assessing the robustness of an estimate, if the estimate of a predictor is associated with the same trend and significance across all FSRs, the estimate of this predictor is to be considered fragile. That is, bank managers will not be able to use that predictor to plan for an improvement in the probability of moving from a current to subsequent bank FSR.

As shown in Table 4.17, CS has negative and statistically significant coefficients at the 1% level for BB, BB+, BBB- and BBB ratings. Also, CS has positive and statistically significant coefficients at the 1% level for BBB+, A- and A ratings and at the 10% level for A+ ratings. The negative sign associated with the predictor estimates confirms that low- and near-low-

FSR banks in the Middle East are undercapitalised. On the contrary, the positive sign associated with the predictor estimates validates that high- and near-high-FSR banks are well capitalised.

This finding act is in accordance with results reported for the capital adequacy and credit risk categories. Table 4.18 shows that CS has a negative and statistically significant coefficient at the 1% level for low- and near-low-FSR banks (e.g., BB, BB+, BBB- and BBB ratings). In addition, CS has positive and statistically significant coefficients at the 1% level for high- and near-high-FSR banks (e.g., BBB+, A- and A ratings). This finding is in harmony with results reported for Model 1.

Table 4.17 indicates that LLRGL has positive and statistically significant coefficients at the 1% level for low- and near-low-FSR banks (e.g., BB, BB+, BBB- and BBB ratings). Also, LLRGL has a negative and statistically significant coefficient at the 1% level for A- ratings and at 10% for BBB+ ratings. This finding is consistent with results reported for the credit risk category. The positive sign associated with the predictor estimates means that low- and near-low-FSR banks have poor quality loan portfolios. On the other hand, the negative sign associated with the predictor estimates implies that near-high-FSR banks are more conservative about selling loans and thus have better quality loan portfolios.

As mentioned previously, this argument is supported by the fact that the average rate of LLRGL for high- and near-high-FSR banks (4.37%) is less than that of low- and near-low-FSR banks (11.11%). It also can be observed in Table 4.18 that LLRGL has a positive and statistically significant coefficient at the 1% level for low- and near-low-FSR banks (i.e., BB, BB+, BBB- and BBB ratings). On the contrary, LLRGL has a negative and statistically significant coefficient at the 1% level for A- ratings and at the 10% level for BBB+ and A+ ratings. This finding is compatible with results reported for Model 1. The negative sign associated with the predictor estimates indicates that high- and near-high-FSR banks implement conservative policies and strategies to amass high quality loan portfolios. Thus, lower loan loss reserve is needed.

As shown in Table 4.17, TME has a negative and statistically significant coefficient at the 1% level for BB, BBB- and BBB ratings and at the 10% level for BB+ ratings. Also, TME has a positive and statistically significant coefficient at the 10% level for BBB+ ratings. This finding validates results reported for the profitability category. The negative sign associated with the predictor estimates shows that low- and near-low-FSR banks inefficiently use security gains or losses and other tax-management tools (e.g., purchase of tax-exempt bonds) to minimise banks' tax exposure. On the contrary, the positive sign associated with the predictor estimates indicates that near-high-FSR banks allocate more funds to invest in tax-exempt financial assets to reduce tax exposure. Table 4.18 shows that TME has a positive and statistically significant coefficient at the 5% level for A+ ratings and at the 10% level for A ratings. The positive sign associated with the predictor estimates indicates that high-FSR banks are capable of minimising their tax exposure and hence generating higher profits than low- and near-low-FSR banks.

As shown in Table 4.17, ECE has a negative and statistically significant coefficient at the 1% level for BB+ and BBB- ratings and at the 5% level for BBB ratings. Also, ECE has a positive and statistically significant coefficient at the 1% level for BBB+, A- and A ratings. The negative sign associated with the predictor estimates indicates that low- and near-low-FSR banks are not expert in reducing bank operating expenses. However, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks implement advanced strategies and policies that assist in reducing operating expenses.

As earlier mentioned, one of these strategies and policies is the introduction of automation systems and mergers and acquisition actions to eliminate overlapping facilities. Finally, this finding complies with results reported for the profitability category. In line with this, Table 4.18 shows that ECE has a negative and statistically significant coefficient at the 1% level for low- and near-low-FSR banks (e.g., BB+, BBB- and BBB ratings). On the other hand, ECE has a positive and statistically significant coefficient at the 1% level for high- and near-high-FSR banks (e.g., BBB+, A- and A ratings). This finding supports the results reported for Model 1.

Table 4.17 shows that TCR has a negative and statistically significant coefficient at the 1% level for BBB ratings, the 5% level for BB ratings and at the 10% level for BBB- ratings. In addition, TCR has a positive and statistically significant coefficient at the 1% level for BBB+, A and A+ ratings and at the 10% level for A- ratings. The negative sign associated with the predictor estimates confirms that low- and near-low-FSR banks in the Middle East are undercapitalised. On the contrary, the positive sign associated with the predictor estimates confirms that high- and near-high-FSR banks are well capitalised and intend to comply with the Basel agreements (i.e., Basel I, II and III). This finding is in line with results reported for the capital adequacy category. In agreement with this, Table 4.18 shows that TCR has a negative and statistically significant coefficient at the 5% level for BBB ratings and at the 10% level for BB ratings. Also, TCR has a positive and statistically significant coefficient at the 5% level for A and A+ ratings and at the 10% level for BBB+ ratings. This finding is in agreement with results reported for Model 1.

Table 4.17 indicates that AU has a negative and statistically significant coefficient at the 1% level for low- and near-low-FSR banks (i.e., BB, BB+, BBB- and BBB ratings). Also, AU has a positive and statistically coefficient at the 1% level for BBB+ ratings. This finding is compatible with results reported for the profitability category. The negative sign associated with the predictor estimates provides further evidence about the incapability of low- and near-low-FSR banks to implement efficient portfolio management policies, especially the mix and yield on assets. However, the positive sign associated with the predictor estimate implies that near-high-FSR banks have succeeded in generating maximum amounts of operating revenue from the available mix of assets. Consistent with this, Table 4.18 shows that AU has a negative and statistically significant coefficient at the 1% level for low- and near-low-FSR banks (i.e., BB, BB+, BBB- and BBB ratings). In additional, AU has a positive and statistically significant coefficient at the 1% level for BBB+ ratings. This finding is compatible with results reported for Model 1.

It can be observed in Table 4.17 that EM has a positive and statistically significant coefficient at the 1% level for BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings. This finding is in agreement with results reported for the capital adequacy category. The positive sign associated with the predictor estimates indicates that banks in the Middle East depend heavily on debt financing rather than equity financing regardless of their assigned FSRs. This is supported by the fact that the historical evolvement of the banking industry in the Middle East has relied mainly on government funding as its main source of equity financing as a substitute for the absence of stock markets in the region during this period. Accordingly, Table 4.18 indicates that EM has a positive and statistically significant coefficient at the 1% level for BB, BB+, BBB-, BBB, BBB+, A-, A and A+ ratings. This finding is in harmony with results reported for Model 1.

Table 4.17 shows that CIR has a positive and statistically significant coefficient at the 1% level for BB and BBB- ratings and at the 5% level for BB+ and BBB ratings. CIR is insignificant for high- and near-high-FSR banks. The positive sign associated with the predictor estimates indicates that low- and near-low-FSR banks implement inadequate strategies to control cost-side activities relative to the generated-income side. It seems that low- and near-low-FSR banks depend entirely on older, labour-based production and delivery systems and hence incur higher overhead and costs (i.e., salaries). This finding confirms results reported by Pasiouras et al. (2006) and Van-Roy (2006). Similarly, Table 4.18 shows that CIR has a positive and statistically significant coefficient at the 5% level for BB ratings and at the 10% level for BB+ and BBB- ratings. This finding is in agreement with results reported for Model 1.

As shown in Table 4.17, LR has a positive and statistically significant coefficient at the 1% level for BB and BBB ratings and at the 5% level for BBB- ratings. Also, LR has a negative and statistically significant coefficient at the 1% level for BBB+ and A ratings and at the 5% level for A- and A+ ratings. In line with Poon et al. (2009), the positive sign associated with the predictor estimates indicates that low- and near-low-FSR banks in the Middle East sell larger amounts of poor quality loans at the expense of their safe liquidity positions. On the contrary, the negative sign associated with the predictor estimates signifies that high- and near-high-FSR banks do not depend entirely on the sale of loans as their main source of revenue. It seems that high- and near-high-FSR banks invest in financial activities to maintain good liquidity positions. These financial activities withstand sudden withdrawals of customers and short-term funding and also yield high returns.

As previously noted, the importance of this ratio has increased significantly since the global financial crisis and Basel III proposed new liquidity requirements to rectify liquidity position within banking industry. In line with this, Table 4.18 reveals that LR has a positive and statistically significant coefficient at the 1% level for BBB- and BBB ratings, at the 5% level for BB+ ratings and at the 10% level for BB ratings. Moreover, LR has a negative and statistically significant coefficient at the 1% level for BBB+, A- and A ratings and at the 5% level for A+ ratings. This finding is consistent with results reported for Model 1.

As revealed in Table 4.17, LLPTL has a positive and statistically significant coefficient at the 10% level for BB+ ratings. The positive sign associated with the predictor estimates denotes that low-FSR banks have poor loan portfolio quality. Accordingly, low-FSR banks are forced to forecast higher estimates of annual provisions relative to total loan portfolio to mitigate future expected loan losses. As seen in Table 4.18, LLPTL has a positive and statistically significant coefficient at the 1% level for BB+ ratings and at the 10% level for BB, BBB- and BBB ratings. On the contrary, LLPTL has a negative and statistically significant coefficient at the 10% level for A- ratings. The negative sign associated with the predictor estimates implies that near-high-FSR banks are more cautious about their loan portfolio quality and thus loan issuance is rigorously monitored and regulated. Consequently, the proportion of annual loan loss provisions to total loan portfolio decreases significantly. This result in a lower credit risk that eventually boosts assigned FSRs. This finding is compatible with the nature of bank operating activities as well as results reported for the credit risk category.

As shown in Table 4.17, LLRIL has a negative and statistically significant coefficient at the 1% level for BB, BB+ and BBB ratings and at the 5% level for BBB- ratings. In addition, LLRIL has a positive and statistically significant coefficient at the 10% level for BBB+ and A- ratings. The negative sign associated with the predictor estimates confirms that low- and near-low-FSR banks do not accumulate an appropriate amount of reserve (either legal or general) to compensate for high balances of impaired loans. Accordingly, the value of bank asset quality declines over time and thus bank FSR deteriorates.

On the contrary, the positive sign associated with the predictor estimates implies that high- and near-high-FSR banks are more enthusiastic and cautious about reserve accumulation than low- and near-low-FSR banks. Eventually, this enhances the value of bank asset quality and therefore bank FSR improves. According to this, Table 4.18 shows that LLRIL has a negative and statistically significant coefficient at the 1% level for BB, BB+ and BBB ratings. In addition, LLRIL has a positive and statistically significant coefficient at the 10% level for BBB+ ratings. This finding is in harmony with results reported for Model 1.

Table 4.17 shows that NIEAA has a positive and statistically significant coefficient at the 5% level for BB ratings. The positive sign associated with the predictor estimates indicates that low-FSR banks suffer from inefficient control over the cost side (overhead plus loan loss provisions) of bank activities relative to assets invested. This finding is line with results reported for CIR and ECE ratios.

Table 4.18 indicates that SR has negative and statistically significant coefficients at the 1% level for low- and near-low-FSR banks (i.e., BB+, BBB- and BBB ratings). Also, SR has a positive and statistically significant coefficient at the 1% level for A and A- ratings and at the 5% level for BBB+ ratings. This finding validates results reported for the asset quality, capital adequacy, credit risk, liquidity and profitability categories. The negative (positive) sign associated with the predictor estimates implies that banks operating in countries with poor (good) macroeconomic factors are assigned low- and near-low (high- and near-high) FSRs.

4.4 Conclusion

This chapter reveals the most consistent and significant financial and nonfinancial variables that are associated with high- and near-high FSRs assigned by CI to banks in the Middle East region. In practice, bank managers as well as stockholders need to focus on the major banking activities and measures (e.g., asset quality, capital adequacy, credit risk, liquidity and profitability) that help achieve high- and near-high FSRs. This understanding is supported by the fact that each RA has its own customised rating system the details of which are not published.

Practitioners as well as researchers can benefit from the information in this chapter as it may help them to design and adjust financial strategies that enable banks in the Middle East achieve high- and near-high FSRs. Banks that seek high- and near-high FSRs should improve their asset quality, profitability and capital adequacy and reduce credit and liquidity risks. In particular, banks in the Middle East should focus on reducing LLRGL, LLPTL, LR, CIR and NIEAA and increasing LLRIL, CS, TCR, TME, ECE and AU. It should also be noted that bank profitability is associated with the highest relative explanatory power in comparison to all other categories. This implies that the CI rating process depends heavily on assessments of bank profitability measures.

This chapter concludes that the addition of nonfinancial variables improves the explanatory power of ML models. The empirical results reveal that a nonfinancial variable, namely SR, plays a crucial role in determining bank FSRs issued by CI in the Middle East. That is, banks that operate in countries with a high SR are assigned high- and near-high FSRs and vice-versa.

CHAPTER 5 PREDICTIVE TECHNIQUES RESULTS

5.1 Introduction

This chapter constructs bank FSR group membership models for banks in the Middle East using three machine-learning techniques—CHAID, CART and MLP neural networks—and two conventional techniques—DA and LR. The reasons for the use of various statistical techniques is to (1) examine whether various results for ACC rates, EMCs and gains charts are achieved; (2) investigate the effects of various data sets, namely the entire data set (351 observations), subsample$_1$ (67% training, 235 observations and 33% testing; 116 observations) and subsample$_2$ (2001-2006 training, 235 observations and 2007-2009 testing; 116 observations) for ACC rates and EMCs; (3) provide the practitioners and researchers with a wide range of bank FSR group membership models that help evaluate the predictive ability of various statistical techniques.

The researcher used 17 financial and nonfinancial variables to predict and discriminate bank FSR group membership. The researcher removed the variables associated with high volumes of missing data. The issue of multicollinearity also is addressed using VIF and a correlation matrix. The variables examined in this chapter are as follows.

(1) LLPNIR, LLRIL and ILGL as proxies for asset quality;

(2) TCR, CS, ENL and EM as proxies for capital adequacy;

(3) NIM, NIEAA, REP, AU and TME as proxies for profitability;

(4) LLPTL as a proxy for credit risk;

(5) LADSTF as a proxy for liquidity; and

(6) SR, size and time as proxies for nonfinancial variables.

The two bank FSR group memberships are mainly high FSR (172 observations) and low FSR (179 observations). The PASW® Modeler 14 was used to run the proposed bank FSR group membership models. This chapter concludes with a comparison of all statistical predictive techniques using different data sets and applying the ACC rate and EMC criteria to provide a sensitivity analysis of the obtained results.

5.2 CHAID

In this section, all CHAID bank FSR group membership models are built using the entire data set (351 observation), $subsample_1$ (67% training, 235 observations and 33% testing; 116 observations) and $subsample_2$ (2001-2006 training, 235 observations and 2007-2009 testing; 116 observations).

5.2.1 Entire data set

The PASW® Modeler 14 was used to design the CHAID bank FSR group membership model using the entire data set and the 17 independent variables. The reason for using the entire data set to build the proposed model is to enable comparison of the results with those of other statistical techniques (i.e., conventional and machine-learning) used in this thesis.

Table 5.1: Classification results for CHAID using entire data set

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	172	166 96.5%	6 3.5%
Low FSR	179	7 3.9%	172 96.1%

Source: Developed by the researcher (based on the statistical output).

Table 5.1 summarises the results for the CHAID bank FSR group membership model using the entire data set. It can be observed that the ACC rate is 96.3% ((166+172)/351), which is the highest ACC rate of all of the conventional and machine-learning statistical techniques employed in this thesis to predict bank FSR group membership. Additionally, of the 172 high FSRs, 166 (96.5%) were predicted to be high FSRs. The predictive accuracy for low FSRs is

96.1% (172/179), which is similar to the figure for high FSRs. The EMC associated with this model is relatively inexpensive (0.256) basically because of a low Type II error rate (3.9%).

5.2.2 Subsample$_1$: 67% training subsample and 33% testing subsample

Following the same method applied to the entire data set, the CHAID bank FSR group membership model utilises all the 17 of the financial and nonfinancial variables to build a model using training subsample$_1$. This is followed by testing the predictive power using testing subsample$_1$.

Table 5.2: Classification results for CHAID using training subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	114	110 96.5%	4 3.5%
Low FSR	121	2 1.7%	119 98.7%

Source: Developed by the researcher (based on the statistical output).

Table 5.2 summarises the classification results for training subsample$_1$ using the CHAID decision-tree technique. The classification matrix in Table 5.2 shows that the ACC rate for training subsample$_1$, for which data are used to fit a model, is 97.4% ((110+119)/235), which is somewhat higher than that of the entire data set (96.3%). Also, the predictive accuracy for low FSRs (98.7%) is superior to that for high FSRs (96.5%). Finally, the EMC associated with the CHAID model using the training subsample$_1$ is 0.119, which is inexpensive EMC because of the minimal percentage of Type II errors (1.7%).

Table 5.3: Classification results for CHAID using testing subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	58	48 82.8%	10 17.2%
Low FSR	58	4 6.9%	54 93.1%

Source: Developed by the researcher (based on the statistical output).

The results reported in Table 5.3 indicate that the ACC rate for testing subsample$_1$, for which the data were used only to test the predictive power of the model, is 87.9% ((48+54)/116). The CHAID model predicts low FSRs (93.1%) better than high FSRs (82.8%). The EMC for testing subsample$_1$ is 0.5, which is more costly than that for the entire data set and training subsample$_1$ as a result of high Type I and II error rates associated with testing subsample$_1$.

5.2.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample

In this section, the CHAID bank FSR group membership model is developed using training subsample$_2$ and testing subsample$_2$. Using the same 17 financial and nonfinancial variables, training subsample$_2$ is used to build the CHAID bank FSR group membership model and testing subsample$_2$ is employed to test the model's predictive power.

Table 5.4: Classification results for CHAID using training subsample$_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	105	100 95.2%	5 4.8%
Low FSR	130	1 0.8%	129 99.2%

Source: Developed by the researcher (based on the statistical output).

Table 5.4 shows the results for CHAID bank FSR group membership model using training subsample$_2$. The ACC rate is 97.4% ((100+129)/235), which is higher than the ACC rate using the entire data set (96.3%) and equal to the ACC rate for training subsample$_1$ (97.4%). In line with training subsample$_1$, the CHAID model using the training subsample$_2$ predicts low FSRs (99.2%) better than high FSRs (95.2%). The EMC for training subsample$_2$ is 0.0723, which is inexpensive mainly because of an insignificant Type II error rate (0.8%).

Table 5.5: Classification results for CHAID using testing $subsample_2$

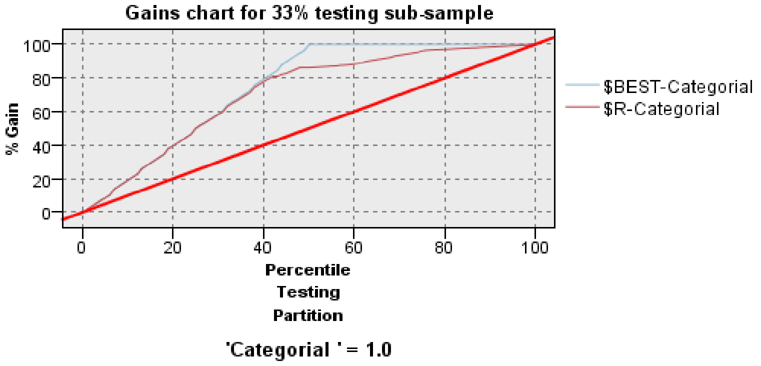
Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	67	61 91%	6 9%
Low FSR	49	7 14.3%	42 85.7%

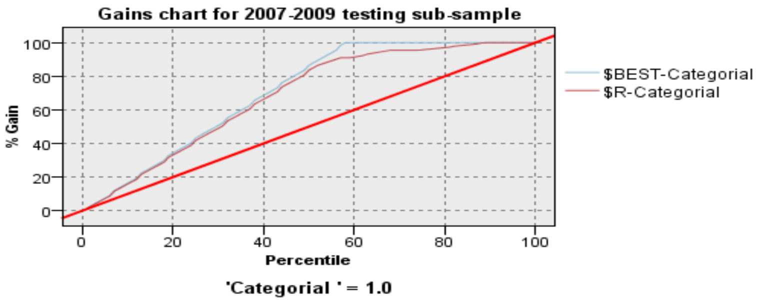
Source: Developed by the researcher (based on the statistical output).

As indicated in Table 5.5, the CHAID bank FSR group membership model using testing $subsample_2$ predicts high FSRs (91%) better than low FSRs (85.7%), which is different from the result reported previously for testing $subsample_1$. The ACC rate using testing $subsample_2$ is 88.8% ((61+42)/116), which is more or less equal to the ACC rate using testing $subsample_1$ (87.9%).

As illustrated in Figure 5.1, the similarity in the ACC rates between both testing subsamples can be observed in the gains charts for testing $subsample_1$ and $subsample_2$, respectively. The EMC for testing $subsample_2$ is 0.776, which is more costly than that for testing $subsample_1$ (0.5). This is supported by the fact that Type II error rates associated with testing $subsample_2$ (14.3%) are almost double than the same rate associated with testing $subsample_1$ (6.9%).

Figure 5.1: Gains charts for testing subsample$_1$ and testing subsample$_2$ using CHAID





5.3 CART

Following the CHAID method explained earlier and using PASW® Modeler 14, all of the selected 17 independent variables were used to build CART bank FSR group membership models using the entire data set, subsample$_1$ (67% training and 33% testing) and subsample$_2$ (2001-2006 training and 2007-2009 testing).

5.3.1 Entire data set

CART bank FSR group membership model is designed using the entire data set and the 17 financial and nonfinancial variables.

Table 5.6: Classification results for CART using entire data set

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	172	163 94.8%	9 5.2%
Low FSR	179	7 3.9%	172 96.1%

Source: Developed by the researcher (based on the statistical output)

As shown in Table 5.6, the CART model reveals a 95.4% ACC rate ((163+172)/351) using the entire data set, which is considered to be the second highest ACC rate across all statistical techniques employed in this thesis, after the ACC rate for the CHAID model (96.3%). Table 5.6 shows that the CART bank FSR group membership model predicts low FSRs (96.1%) somewhat better it predicts high FSRs (94.8%). The EMC associated with the CART model using entire data set is 0.265, which is costly than that associated with the CHAID model (0.256) using the same data set.

5.3.2 Subsample$_1$: 67% training subsample and 33% testing subsample

Following the same method employed for the entire data set, training subsample$_1$ with all 17 independent variables was used to fit the CART bank FSR group membership model. Consequently, testing subsample$_1$ tests the predictive effectiveness of the fitted model.

Table 5.7: Classification results for CART using training subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	114	111 97.4%	3 2.6%
Low FSR	121	4 3.3%	117 96.7%

Source: Developed by the researcher (based on the statistical output)

Table 5.7 indicates that the ACC rate for training subsample$_1$, *for which the data are used to build a model*, is 97% ((111+117)/235), which is higher than the ACC rate for the entire data set (95.4%). It can be observed that the CART bank FSR group membership model classifies high FSRs with slightly better predictive accuracy than it does low FSRs (97.4% and 96.7%, respectively). The EMC associated with the CART model for training subsample$_1$ is 0.217, which considered more expensive than the EMC associated with CHAID model for the same subsample (0.0119). This is supported by the fact that the Type II error rate associate with the CART model (3.3%) is almost double the rate associated with CHAID model (1.7%) for training subsample$_1$.

Table 5.8: Classification results for CART using testing subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	58	52 89.7%	6 10.3%
Low FSR	58	3 5.2%	55 94.8%

Source: Developed by the researcher (based on the statistical output).

Table 5.8 summarises the classification results for testing subsample$_1$ using the CART technique. The classification matrix in Table 5.8 shows that the ACC rate for testing subsample$_1$, *for which the data played no role in fitting the model*, is 92.2% ((52+55)/116). Because CART and CHAID are decision-tree techniques, it is worth noting that the ACC rate associated with the CART model is higher than that associated with the CHAID model (87.9%) for testing subsample$_1$. This is supported by the fact that the predictive accuracy of the CART model for high and low FSRs (89.7% and 94.8%, respectively) is higher than the predictive accuracy of the CHAID model for high and low FSRs (82.8% and 93.1%, respectively). In line with this, the EMC associated with the CART model (0.362) is less costly than the EMC associated with CHAID model (0.5) for testing subsample$_1$.

5.3.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample

In this section, using the same 17 financial and nonfinancial variables, the CART bank FSR group membership model is built using training subsample$_2$ and is tested using testing subsample$_2$.

Table 5.9: Classification results for CART using training subsample$_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	105	102 97.1%	3 2.9%
Low FSR	130	4 3.1%	126 96.9%

Source: Developed by the researcher (based on the statistical output).

Table 5.9 shows the classification results for training subsample$_2$ using the CART technique. Table 5.9 reveals that the ACC rate is 97% ((102+126)/235), which is equal to the ACC rate associate with CHAID using the same subsample. Unlike the CHAID model, the predictive accuracy of the CART model for high FSRs (97.1%) is somewhat higher than the predictive accuracy for low FSRs (96.9%). In line with this, using training subsample$_{2,}$ the EMC associated with the CART model (0.217) is more costly than the EMC associated with CHAID model (0.072). This is mainly a result of the fact that the Type II error rate for the CART model (3.1%) is four times greater than the type II error rate for the CHAID model (0.8%).

Table 5.10: Classification results for CART using testing subsample$_2$

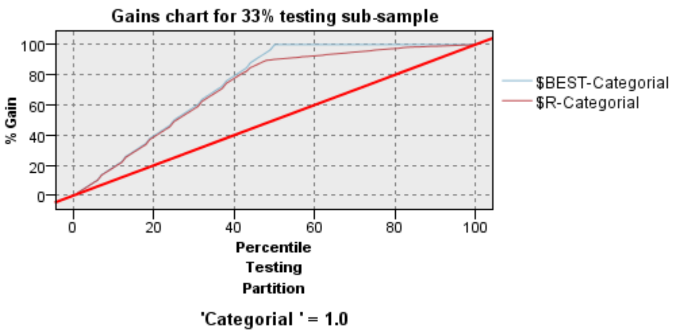
Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	67	55 82.1%	12 17.9%
Low FSR	49	8 16.3%	41 83.7%

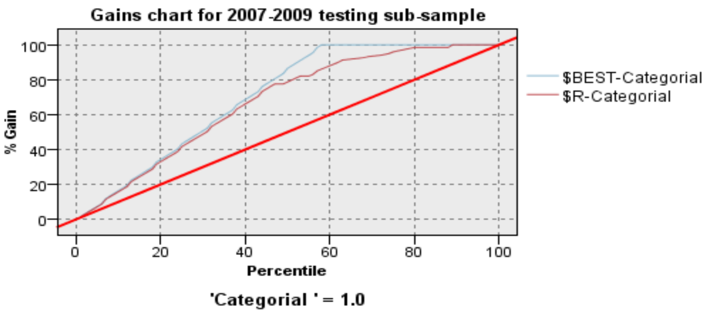
Source: Developed by the researcher (based on the statistical output).

From results revealed in Table 5.10, the ACC rate associated with the CART model using the testing subsample$_2$ is 82.8% ((55+41)/116). This ACC rate is lower than the ACC rate associated with the CHAID model (88.8%) for the same sample. In addition, it is significantly lower than the ACC rate associated with the CART model (92.24%) using the testing subsample$_1$.

As shown in Figure 5.2, the difference between CART models using testing subsample$_1$ and testing subsample$_2$ can be observed clearly in the graphical analysis. This significant decline in the ACC rate is mainly a result of the lower predictive power of the CART model (82.1% for high FSRs and 83.7% for low FSRs) using testing subsample$_2$. Accordingly, the EMC associated with the CART model using testing subsample$_2$ (0.931) is more expensive than the EMC associated with the CHAID model using the same subsample (0.776).

Figure 5.2: Gains charts for testing subsample$_1$ and testing subsample$_2$ using CART





5.4 Multilayer perceptron neural networks

In this section, MLP models are developed because of the categorical nature of the dependent variable. MLP bank FSR group membership models are designed using the same 17 financial and nonfinancial variables listed earlier for the entire data set, $subsample_1$ (training and testing) and $subsample_2$ (training and testing).

5.4.1 Entire data set

The PASW® Modeler 14 was used in this thesis to design the MLP bank FSR group membership model using the entire data set and the 17 independent variables.

Table 5.11: Classification results for MLP neural network using entire data set

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	172	158 91.9%	14 8.1%
Low FSR	179	7 3.9%	172 96.1%

Source: Developed by the researcher (based on the statistical output).

Table 5.11 presents the classification results for the MLP bank FSR group membership model for the entire data set. Table 5.11 indicates that the ACC rate is 94.02% ((158+172)/351), which is the lowest ACC rate across all other machine-leaning techniques employed in this thesis to predict banks' FSR group memberships (i.e., CHAID and CART). Moreover, of the 172 high FSRs, 158 (91.9%) were predicted to be high FSRs. The predictive accuracy for low FSRs is exceptional at 96.1% (172/179). The EMC associated with the MLP model is more costly (0.279) than the EMCs associated with other machine-learning techniques, namely, CHAID (0.256) and CART (0.265). This is supported by the fact that the Type I error rate is significantly higher for the MLP model than for other machine-learning techniques.

5.4.2 Subsample$_1$: 67% training subsample and 33% testing subsample

In line with the same method used in the entire data set MLP section, and using only training subsample$_1$, all of the 17 independent variables were used to build the MLP bank FSR group membership model. Testing subsample$_1$ was used to test the predictive power of the fitted model.

Table 5.12: Classification results for MLP neural network using training subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	114	110 96.4%	4 3.6%
Low FSR	121	10 8.3%	111 91.7%

Source: Developed by the researcher (based on the statistical output).

As seen in Table 5.12, the MLP model predicts high FSRs (96.4%) better than it does lower FSR banks (91.7%) using training subsample$_1$. Consequently, the ACC rate for training subsample$_1$, *for which data are used to fit a model*, is 94.0% ((110+111)/235), which is lower than the ACC rates associated with CHAID (97.4%) and CART (97.02%) using the same subsample$_1$.

Accordingly, the EMC associated with the MLP model using training subsample$_1$ is 0.528. It is the most costly EMC of those associated with the two other machine-learning techniques using same subsamples$_1$. Apparently, the high Type II error rate (8.3%) associated with the MLP model enlarges the overall EMC of the model.

Table 5.13: Classification results for MLP neural network using testing subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	58	53 91.4%	5 8.6%
Low FSR	58	11 19%	47 81%

Source: Developed by the researcher (based on the statistical output).

Table 5.13 shows the classification results for testing $subsample_1$ using the MLP neural network model. The classification matrix in Table 5.13 indicates that the ACC rate for testing $subsample_1$, *for which the data are used only to test the predictive power of the model*, is 86.21% ((53+47)/116). The MLP neural network model predicts high FSRs (91.4%) better than it does low FSRs (81%). The EMC associated with the MLP model using testing $subsample_1$ (1.181) is much more expensive than the EMCs associated with CHAID (0.5) and CART (0.362) using same testing $subsample_1$. Apparently, the high Type II error rate (19%) associated with the MLP model enlarges its EMC.

5.4.3 $Subsample_2$: 2001-2006 training subsample and 2007-2009 testing subsample

The same validation technique used for the entire data set and $subsample_1$ is repeated for $subsample_2$ using the original 17 independent variables.

Table 5.14: Classification results for MLP neural network using training $subsample_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	105	100 95.2%	5 4.8%
Low FSR	130	7 5.4%	123 94.6%

Source: Developed by the researcher (based on the statistical output).

Table 5.14 summarises the results for MLP bank FSR group membership model using training $subsample_2$.The ACC rate using training $subsample_2$ is 94.9% ((100+123)/235), which is lower than the ACC rates using same training $subsamples_2$ for both CHAID (97.4%) and CART (97.02%). The MLP model, using training $subsample_2$, predicts high FSRs (95.2%) better than it does low FSRs (94.6%). The EMC for training $subsample_2$ is 0.379, which is significantly more expensive than the EMCs associated with both CHAID (0.072) and CART (0.217) using same training $subsamples_2$.

Table 5.15: Classification results for MLP neural network using testing subsample$_2$

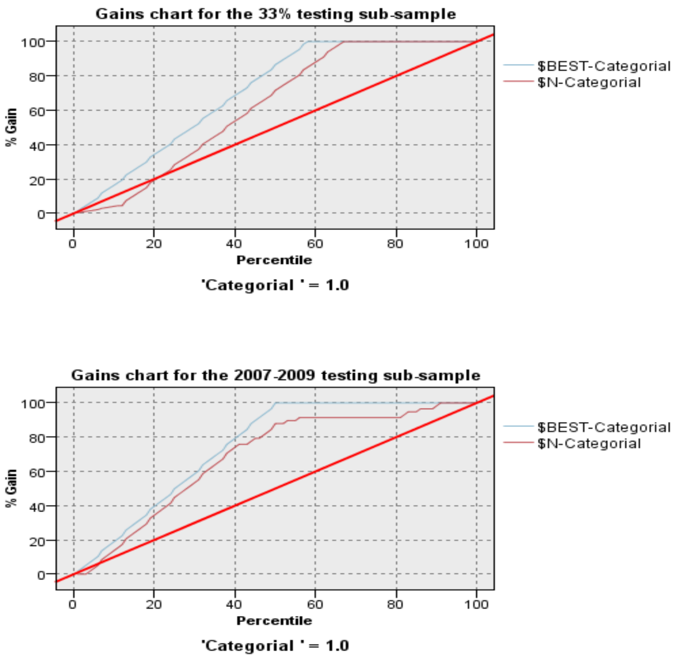
Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	67	54 80.6%	13 19.4%
Low FSR	49	9 18.4%	40 81.6%

Source: Developed by the researcher (based on the statistical output)

As shown in Table 5.15, the MLP bank FSR group membership model, using testing subsample$_2$, predicts low FSRs (81.6%) slightly better than it does high FSRs (80.6%), which is different from results reported previously for testing subsample$_1$. The ACC rate using testing subsample$_2$ is 81% ((54+40)/116), which is lower than the ACC rate for testing subsample$_1$ (86.21%). This is supported by the fact that the predictive capability of the MLP model for high FSRs using testing subsample$_2$ (80.6%) declined significantly in contrast to that using testing subsample$_1$ (91.4%).

As illustrated in Figure 5.3, the difference in the ACC rates between both testing subsamples can be observed in the gains charts for testing subsample$_1$ and testing subsample$_2$. Finally, the EMC for testing subsample$_2$ is 1.04 that is relatively less costly to that for testing subsample$_1$ (1.181).

Figure 5.3: Gains charts for testing subsample$_1$ and testing subsample$_2$ using MLP neural network



5.5 Discriminant analysis

According to the method adopted in this thesis, one linear discriminating function with its **Z** index (**Z** model) is derived. This procedure develops a set of discriminating functions that helps predict bank FSR group memberships in the Middle East region based on 17 bank financial and nonfinancial variables using the entire data set, subsample$_1$ (training and testing) and subsample$_2$ (training and testing).

5.5.1 Entire data set

The stepwise selection algorithm produces certain significant variables as predictors of grouping. The forward stepwise approach ensures that at each step the variable that minimises the overall Wilk's lambda will be entered. The minimum partial *F* to enter is 3.84, and the minimum partial *F* to remove is 2.71. Prior probabilities are computed from group sizes[68] and

[68]As mentioned earlier, low-FSR banks had 179 observations and high-FSR banks had 172 observations.

the covariance matrix is applied within groups. The one discriminating function with *p*-value < 0.05 is statistically significant at the 99% confidence level. Table 5.16 presents the discriminating function with its standardised coefficients for bank financial and nonfinancial variables using the entire data set.

Table 5.16 reports the significant coefficients of bank financial and nonfinancial variables that discriminate between high- and low-FSR group memberships using the entire data set. The large Eigenvalue (5.018) presented in Table 5.16 indicates that the estimated discriminant model has high discriminating ability. A canonical correlation of 0.913 suggests that the model explains 83.4% of the variation in the grouping variables. A small value for Wilk's lambda (0.166) means that only 16.6% of the total variability is unexplained.

The results show that eight financial and three nonfinancial variables are statistically significant. The financial variables are the ratio of loan loss provision to net interest revenue (LLPNIR) and the ratio of impaired loans to gross loans (ILGL) as proxies for the asset quality category; bank CS, total capital ratio (TCR) and the ratio of equity to net loans (ENL) as proxies for capital adequacy category; asset utilisation (AU) and the ratio of recurring earning power (REP) as proxies for profitability; and the ratio of loan loss provision to total loans (LLPTL) as a proxy for credit risk. The nonfinancial variables are bank size, country SR and time effect (T).

Table 5.16: The components of discriminant model for low-and high-FSR group membership

Components of the Z model	Coefficients[69]
Bank capital structure (CS)	0.229
Asset utilisation (AU)	0.602
Loan loss provision to net interest revenue (LLPNIR)	-0.409
Impaired loans to gross loans (ILGL)	-0.367
Total capital ratio (TCR)	0.380
Equity to net loans (ENL)	0.464
Recurring earning power (REP)	0.330
Loan loss provision to total loans (LLPTL)	-0.606
Country sovereign rating (SR)	0.650
Size	0.789
T	-0.343
Eigenvalue[70]	5.018
% of variance	100%
Canonical correlation[71]	0.913
Wilks Lambda[72]	0.166
χ^2	428.053*
n	351

* Significant at the 1% level.
Source: Developed by the researcher (based on the statistical output).

The results show a considerable degree of consistency as the coefficients of CS, TCR, ENL, AU and REP are associated with a positive sign. The positive sign associated with the CS coefficient denotes that high-FSR banks are well capitalised. This also is confirmed by the positive sign associated with the TCR and ENL coefficients. The positive sign associated with the AU coefficient indicates that high-FSR banks efficiently utilise their assets. The positive sign associated with the REP coefficient confirms that high-FSR banks generate an

69 Standardised canonical discriminant function coefficients provide an index of the importance of each variable as did the standardised regression coefficients (betas) in multiple regression. The sign indicates the direction of the relationship.
70 The variance in a set of variables explained by a factor or component and denoted by lambda. An Eigenvalue is the sum of squared values in the column of a factor matrix, or $\lambda_k = \sum_{t-1}^{m} a_k^2$ where a_{ik} is the factor loading for variable *i* on factor k, and m is the number of variables. Simply, this figure represents the ratio of the between-group sums of the square to the within-group sum of squares of the discriminant scores.
71 Canonical correlation is the multiple correlations between the variables and the discriminant function.
72 Wilk's Lambda provides a test by which to assess the null hypothesis, which in the population, the vectors of means of financial and nonfinancial variables is the same in the two groups. Thus, this figure indicates a highly significant function and provides the proportion of total variability not explained (i.e., the converse of the squared canonical correlation).

appropriate amount of income even after adding provisions for loan losses from their available assets.

On the contrary, the negative signs associated with the LLPTL and LLPNIR coefficients suggest that high-FSR banks employ robust credit management techniques and compensate large numbers of risky loans with greater interest margins. Consequently, the ratios of loan loss provision to either total loans or net interest revenue for high-FSR banks are lower than the comparable ratios for low-FSR banks. In line with this, the negative sign associated with the ILGL coefficient confirms that high-FSR banks have better quality loan portfolios than the low-FSR banks. Consequently, the amount of impaired loans as a percentage of gross loans for high-FSR banks is less than the same figure for low-FSR banks.

With regard to nonfinancial variables, the positive sign associated with the SR coefficient implies that high-FSR banks operate in countries associated with relatively stable financial and economic conditions (Poon and Firth, 2005; Poon et al., 2009; Van-Roy, 2006). In addition, the positive sign associated with the size coefficient indicates that high-FSR banks are relatively large in size (Pasiouras et al., 2006). On the contrary, the negative sign associated with the coefficient of the time dummy variable implies that FSRs of Middle East banks deteriorated slightly during the period from 2001 to 2009.[73]

Figure 5.4 shows two histograms that illustrate the distribution of discriminant function scores for each group membership. The range of scores on the axes, including the means of both and the very minimal overlap of the graphs, reveals substantial discriminatory power.[74] This implies that the function discriminates well as indicated in Table 5.16.

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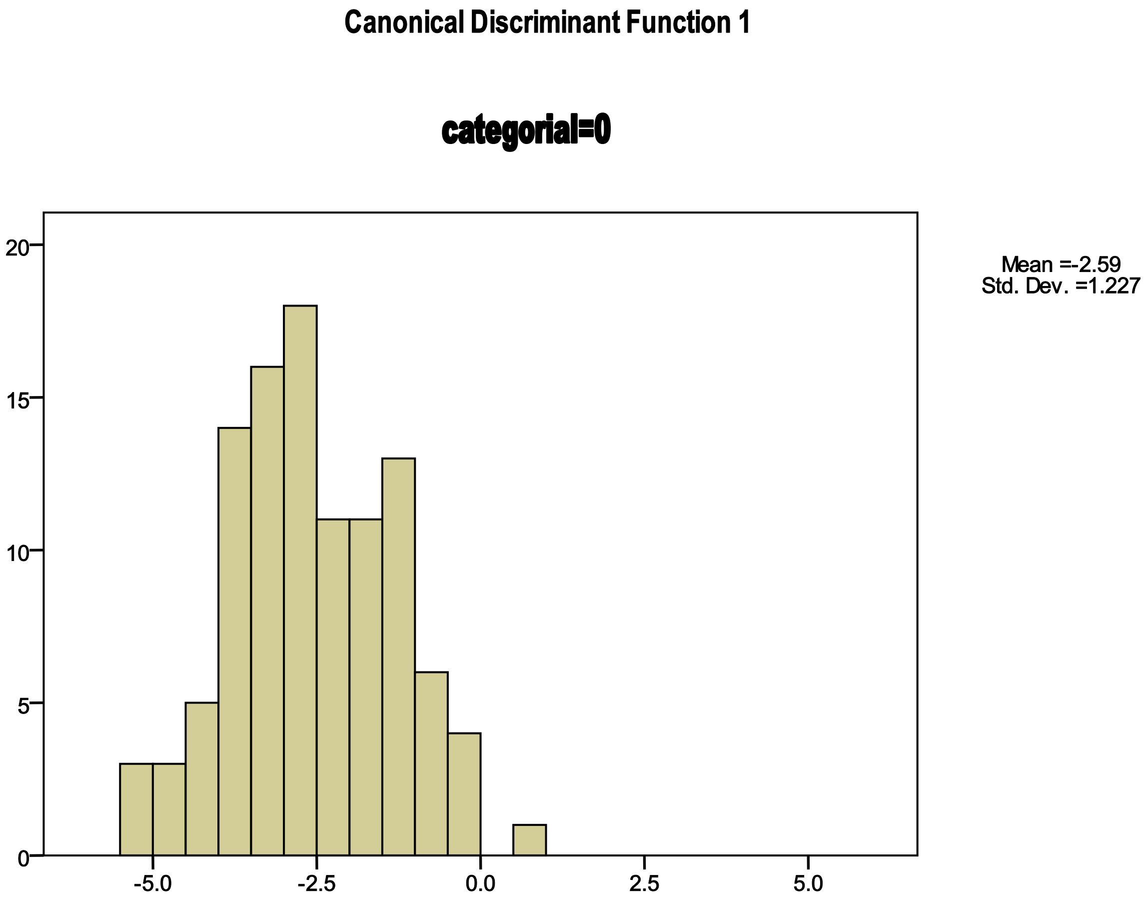
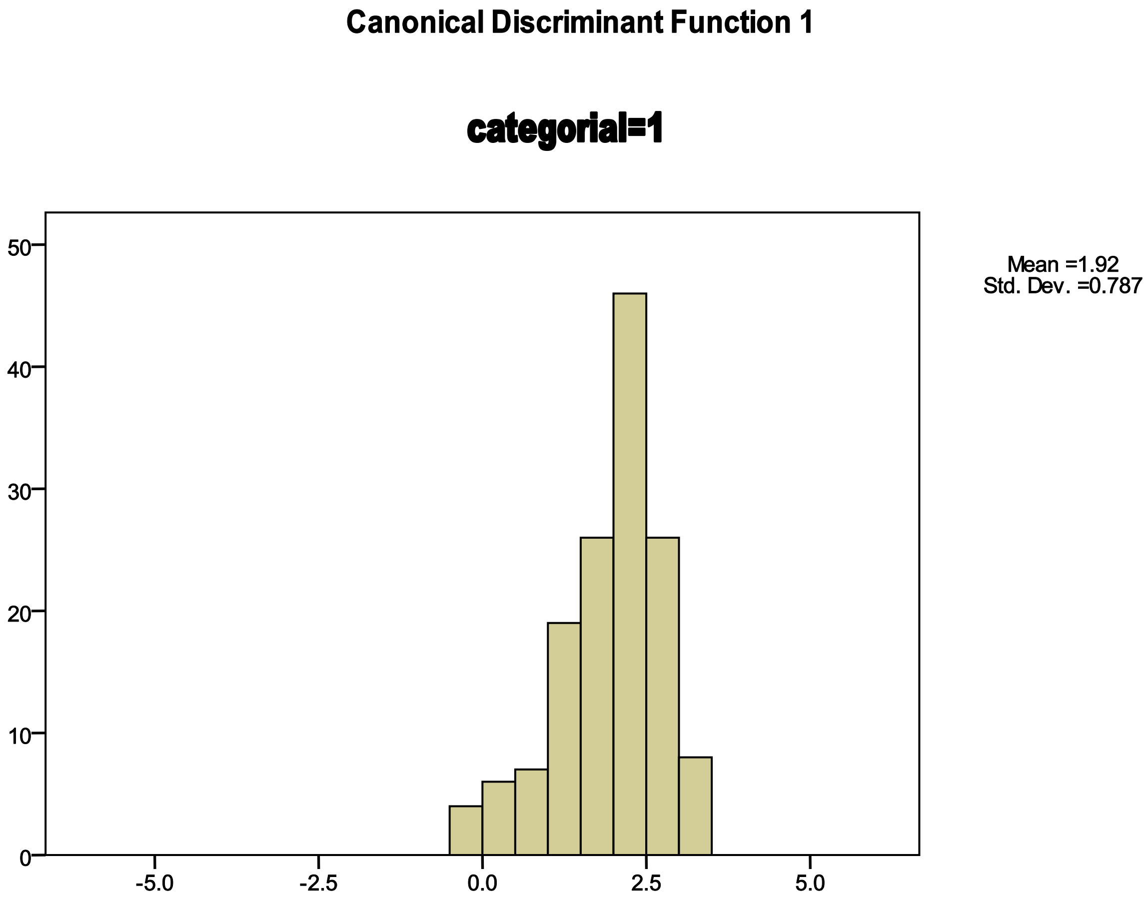
[73] It is worth mentioning that the stepwise algorithm used in the ML regression produced a positive sign associated with the time variable. In terms of robustness, it is evident that the time variable is fragile. That is, the decision maker has to exercise caution when using the time variable to make rating decisions.

[74] An alternative way to interpret the discriminant analysis results is to describe each group in terms of its profile, using the group means of the independent variables. These group means are called centroids. That is,

Figure 5.4: Histograms showing the distribution of discriminant scores for low- and high-FSR group memberships



low-FSR banks have a mean of -2.585 and high-FSR banks have a mean of 1.925. Cases with scores near a centroid are predicted to belong to that group.



Because the two groups are not in equal size, the estimated prior probability ratios are 0.51 for group 1 and 0.49 for group 2.[75] The researcher calculated the cut-off point on the **Z**-scale using the estimated prior probability ratios. The cut-off point on the **Z**-scale is shown in Table 5.17. The cut-off point is calculated as Ln (P1/P2), where P1 = the prior probability of low-FSR banks and P2 = the prior probability of high-FSR banks.

Table 5.17: The cut-off point for low- versus high-FSR group membership

Prior Probability	Low-FSR banks	High-FSR banks	Cut-Off Point
Bank FSR (low versus high)	0.51	0.49	0.0398

[75] The prior probability ratio is an estimate of the proportion of banks with a ratio profile similar to that of groups 1 and 2.

5.5.1.1 Relative contribution of the model's discriminatory power

The usefulness of DA requires the profile of the final variables to show the relative contribution of each variable to the total discriminating power of the **Z**-score model and the interaction between them. The common approach used to assess the relative contribution is based on a measurement of the proportion of the Mahalanobis $\mathbf{D}^2$-distance between the centroids of the two constituent groups accounted for by each variable (Mosteller and Wallace, 1963; Taffler, 1983).[76]

Table 5.18: Relative contribution of the models' discriminatory power

Components of the Z model	Relative Contribution *	
Financial variables		
Loan loss provision to net interest revenue (LLPNIR)	7.90%	
Impaired loans to gross loans (ILGL)	7.09%	
Total capital ratio (TCR)	7.35%	
Bank capital structure (CS)	4.42%	65.5%
Equity to net loans (ENL)	8.98%	
Recurring earning power (REP)	6.39%	
Asset utilisation (AU)	11.65%	
Loan loss provision to total loans (LLPTL)	11.72%	
Nonfinancial variables		
Time effect (T)	6.64%	
Sovereign rating (SR)	12.58%	34.5%
Bank size (Size)	15.26%	

Note. * Mosteller-Wallace measure.
Source: Developed by the researcher (based on the statistical output).

Table5.18 reveals that all financial variables (LLPNIR, ILGL, TCR, CS, ENL, REP, AU and LLPTL) contribute to the model's discriminatory power by 65.5%, and nonfinancial variables

[76] $P_j = \dfrac{c_j\left(\bar{r}_{jf} - \bar{r}_{js}\right)}{\sum_{i=1}^{4} c_i\left(\bar{r}_{if} - \bar{r}_{is}\right)}$ where P_j = The proportion of the D^2-distance accounted for by ratio j

$\bar{r}_{if}$ and $\bar{r}_{is}$ = The means of the below-median and above-median groups for ratio i respectively.

(size, SR and T) contribute to the model's discriminatory power by 34.5%. This outcome shows that financial variables contribute more than nonfinancial variables to the overall discriminatory power. This finding implies that bank managers must give relatively higher weight to the financial rather than nonfinancial variables when they formulate bank policies and strategies.

For financial variables, LLPTL, AU and ENL have a relatively high contribution to the model's discriminatory power (11.72%, 11.65% and 8.98%, respectively). The overall contribution of the three financial variables to bank FSRs is 32.35%. That is, when it comes to bank FSRs in the Middle East, RAs depend mainly on the following three aspects: (1) the extent to which the banks utilise their available assets efficiently; (2) the extent to which banks use leverage to finance their lending activities and (3) the quality of banks' loan portfolios. With regard to nonfinancial variables, bank size and SR contribute much to the model's discriminatory power (15.26% and 12.58%, respectively). This result indicates that RAs assign more weight for bank size and country SR in the process of assigning bank FSRs in the Middle East.

5.5.1.2 Classification matrix of discriminant analysis using entire data set

Table 5.19: Classification results for discriminant analysis using entire data set

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	172	166 96.5%	6 3.5%
Low FSR	179	18 10%	161 90%

Source: Developed by the researcher (based on the statistical output).

The final results of the classification matrix using the entire data set are shown in Table 5.19. High FSRs are classified with slightly better accuracy (96.5%) than low FSRs (90%). As indicated in Table 5.19, Type I and II error rates are less than ACC rates for both levels of low and high FSRs. This is considered to support the relatively high reliability of the estimated discriminant models.

Table 5.19 shows that the model's classification accuracy reaches a high degree of ACC rate and reveals that 93.16% ((161+166)/351) of respondents were classified correctly into high- or low-FSR groups. The EMC for the entire data set using DA is 0.632.

5.5.2 Subsample$_1$: 67% training subsample and 33% testing subsample

Following the same method used for the entire data set, training subsample$_1$ with all 17 financial and nonfinancial variables is used to build the DA bank FSR group membership model. Tests of subsample$_1$ check the predictive effectiveness of the fitted model.

Table 5.20: Classification results for discriminant analysis using training subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	114	111 97.4%	3 2.6%
Low FSR	121	11 9.1%	110 90.9%

Source: Developed by the researcher (based on the statistical output).

Table 5.20 summarises the classification results for training subsample$_1$ using the DA technique. In line with the results for the entire data set, high FSRs were classified with greater accuracy (97.4 %) than low FSRs (90.9%). From the results reported in Table 5.20, the ACC rate for training subsample$_1$, *for which the data are used to fit a model*, is 94.04% ((110+111)/235), and the EMC associated with this model using training subsample$_1$ is 0.574.

Table 5.21: Classification results for discriminant analysis using testing subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	58	55 94.8%	3 5.2%
Low FSR	58	13 22.4%	45 77.6%

Source: Developed by the researcher (based on the statistical output).

Table 5.21 reports the classification results for testing subsample$_1$, *for which the data play no role in model-fitting*. Along the lines of the entire data set and training subsample$_1$, high FSRs are classified with greater accuracy (94.8%) than low FSRs (77.6%). The ACC rate for testing subsample$_1$ is 86.21% ((45+55)/116). The EMC for testing subsample$_1$ is 1.37, which is costly because of the high type II error rate (22.4%).

5.5.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample

The same method used for the entire data set and subsample$_1$ was repeated for subsample$_2$ using the original 17 financial and nonfinancial variables.

Table 5.22: Classification results for the discriminant analysis using training subsample$_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	105	104 99.0%	1 1%
Low FSR	130	14 10.7%	116 89.2%

Source: Developed by the researcher (based on the statistical output).

Table 5.22 shows that the ACC rate for training subsample$_2$, *in which the data are used to build the model*, is 93.62% ((116+104)/235). The ACC rates for DA models for the entire data set, training subsample$_1$ and training subsample$_2$ are similar. Furthermore, high FSRs were classified with much higher accuracy (99%) than low FSRs (89.2%). High-FSR classification accuracy percentages are superior to these associated with low FSRs for the same three samples. The EMC associated with training subsample$_2$ is relatively costly (0.719) compared to that for training subsample$_1$ (0.574). This is supported by the fact that the Type II error rate for the training subsample$_2$ (10.7%) is slightly greater than that of training subsample$_1$ (9.1%).

Table 5.23: Classification results for discriminant analysis using testing subsample$_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	67	59 88.1%	8 11.9%
Low FSR	49	1 2%	48 98%

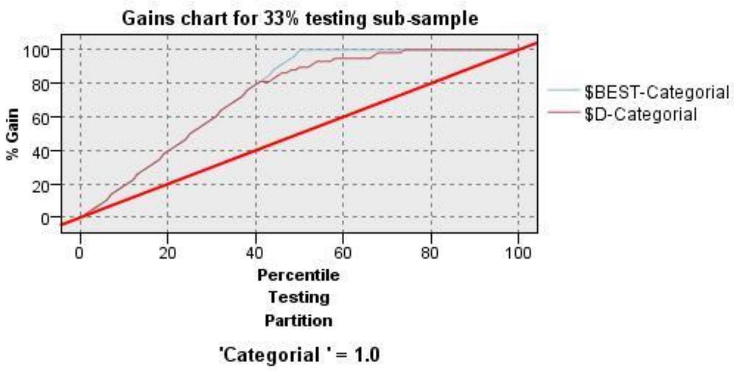
Source: Developed by the researcher (based on the statistical output).

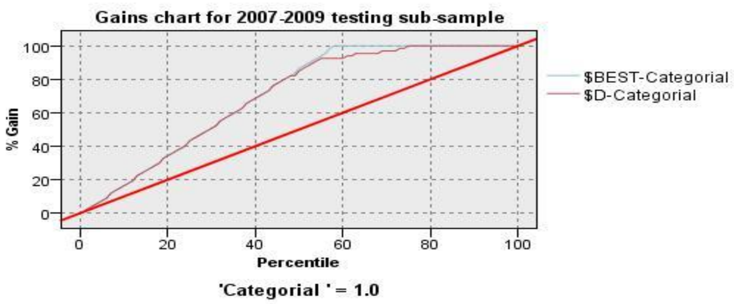
Table 5.23 presents the classification results for testing subsample$_2$, *i.e. for which the data play no role for building the model*. Unlike results reported earlier under the entire data set and testing subsample$_1$, low-FSR is classified with superior accuracy (98%) than high-FSR (88.1%). The ACC rate for the testing subsample$_2$ is 92.24% ((48+59)/116). That is, testing subsample$_2$ performs better in terms of correct classification and prediction accuracy than testing subsample$_1$.

In line with this, the EMC associated with testing subsample$_2$ (0.172) is significantly lower than that associated with testing subsample$_1$ (1.37). This is mainly because, as shown in Table 5.23, type I error rate exceeds type II error rate and thus reduces the misclassification cost for testing subsample$_2$ relative to that of testing subsample$_1$. Differences between testing subsample$_1$ and testing subsample$_2$ can be observed in the graphical analysis in Figures 5.5.

Figure 5.5 presents the gains charts for testing subsample$_1$ and testing subsample$_2$ using discriminant analysis. It is obvious that the gains curve for testing subsample$_2$ is steeper than that for testing subsample$_1$. This finding is supported by the fact that the ACC for testing subsample$_2$ (92.24%) is better than the ACC for testing subsample$_1$ (86.21%).

Figure 5.5: Gains charts for testing subsample$_1$ and testing subsample$_2$ using discriminant analysis





5.6 Logistic regression

LR models are developed to describe the relationship between the categorical dependent variable (high-FSR versus low-FSR banks) and the 17 financial and nonfinancial variables using the entire data set, subsample$_1$ (training and testing) and subsample$_2$ (training and testing).

5.6.1 Entire data set

Following the LR method explained earlier and using the PASW® Modeler 14, the forward stepwise approach was employed to build LR bank FSR group membership models using the entire data set. The statistical characteristic of model fitting (see Appendix D) shows that the final model is significant at the 1% level (χ^2 = 324.936; df = 18) and thus confirms a statistically significant relationship between the variables at the 99% confidence level.

Table 5.24: Classification results for LR using entire data set

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	172	140 81.4%	32 18.6%
Low FSR	179	61 34.1%	118 65.9%

Source: Developed by the researcher (based on the statistical output).

Table 5.24 reports the results of the LR bank FSR group membership model for the entire data set. The LR model reveals a 73.5% ACC rate ((140+118)/351), which is the lowest ACC rate across all of the statistical techniques (i.e., conventional and machine-learning) used in this thesis. As shown in Table 5.24, the LR model predicts high FSRs (81.4%) better than it does low FSRs (65.9%). The EMC associated with LR model using the entire data set is 2.177, which is the most expensive EMC across all of the statistical techniques used in this thesis. This is mainly a result of high Type II errors associated with the LR model.

5.6.2 Subsample$_1$: 67% training subsample and 33% testing subsample

The main objective of this section is to examine whether different results in terms of ACC rates and EMCs are achieved using different sample sizes. Following the same method employed for the entire data set, training subsample$_1$ with all 17 independent variables is used to fit the LR bank FSR group membership model. Subsequently, testing subsample$_1$ tests the predictive effectiveness of the fitted model.

Table 5.25: Classification results for LR using training subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	114	111 97.4%	3 2.6%
Low FSR	121	22 18.2%	99 81.8%

Source: Developed by the researcher (based on the statistical output).

As revealed in Table 5.25, the ACC rate for training subsample$_1$, *for which data are used to building a model*, is 89.36%, which is higher than the ACC rate for the entire data set (73.5%). It can be observed that the LR bank FSR group membership model classifies high FSRs with greater predictive accuracy than it does low FSRs (97.4% and 81.8%, respectively).

The EMC associated with the LR model for training subsample$_1$ is 1.136, which is almost double the EMC associated with discriminant analysis model for the same subsample (0.574). This is supported by the fact that the Type II error rate associated with the LR model (18.1%) is almost double the same rate associated with the DA model (9.1%) using training subsample$_1$.

Table 5.26: Classification results for LR using testing subsample$_1$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	58	53 91.4%	5 8.6%
Low FSR	58	12 20.7%	46 79.3%

Source: Developed by the researcher (based on the statistical output).

Table 5.26 summarises the classification results for testing subsample$_1$ using the LR technique. The classification matrix in Table 5.26 shows that the ACC rate for testing subsample$_1$, *for which data played no role in fitting the model*, is 85.34% ((53+46)/116). Because DA and LR are conventional techniques, it is worth noting that the ACC rate associated with the DA model (86.21%) is higher than that associated with the LR model using testing subsample$_1$.

Similar to results reported using the entire data set and training subsample$_1$, the predictive accuracy of the LR model for predicting high FSRs (91.4%) is higher than for low FSRs (79.3%). The EMC associated with the LR model (1.284) is relatively inexpensive compared to the EMC associated with the discriminant analysis model (1.37) using same subsample$_1$.

5.6.3 Subsample$_2$: 2001-2006 training subsample and 2007-2009 testing subsample

Using the same 17 financial and nonfinancial variables, the LR model in this section is built using training subsample$_2$ and is tested using testing subsample$_2$.

Table 5.27: Classification results for LR using training subsample$_2$

Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	105	78 74.3%	27 25.7%
Low FSR	130	61 46.9%	69 53.1%

Source: Developed by the researcher (based on the statistical output).

Table 5.27 reveals that the ACC rate associated with the LR model using training subsample$_2$ is 62.55% ((78+69)/235), which is significantly lower than the ACC rate associated with the DA using the same subsample. Along the lines of the DA model using training subsample$_2$, the predictive accuracy of the LR model for high FSRs (74.3 %) is higher than the predictive accuracy for low FSRs (53.1%).

The EMC associated with the LR model (3.23) is significantly expensive compared to the EMC associated with DA model (0.719) using training subsample$_2$.This is mainly a result of the fact that the Type II error rate for the LR model (46.9%) is almost five times greater than Type II error rate for the DA model (10.7%).

Table 5.28: Classification results for LR using testing subsample$_2$

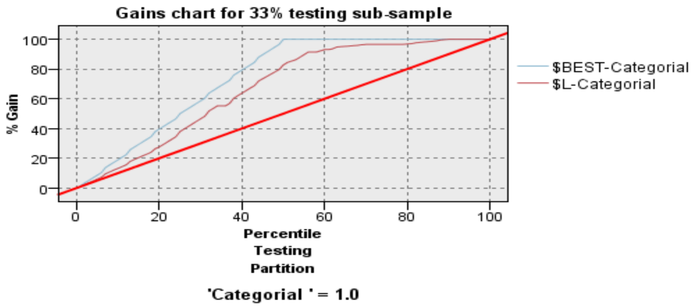
Actual Group Membership	No. of Cases	Predicted Group Membership	
		High FSR	Low FSR
High FSR	67	16 23.9%	51 76.1%
Low FSR	49	19 38.8%	30 61.2%

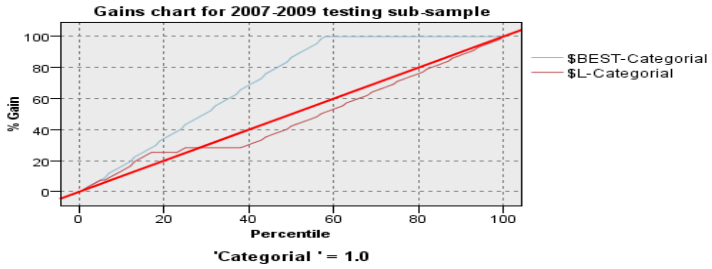
Source: Developed by the researcher (based on the statistical output).

As seen in Table 5.28, the ACC rate associated with the LR model using testing subsample$_2$ is 39.66% ((16+30)/116). Apparently, this ACC rate is the lowest ACC rate across all conventional and machine-learning techniques employed in this thesis using any data set. In addition, this rate is significantly lower than the ACC rate associated with the LR model (85.34%) using testing subsample$_1$.

As shown in Figure 5.6, the difference between LR models using testing subsample$_1$ and testing subsample$_2$ can be observed clearly in the graphical analysis. For testing subsample$_2$, the significant decline in the ACC rate is mainly a result of the lower predictive power of the LR model (23.9% for high FSRs and 61.2% for low FSRs). Accordingly, the EMC associated with the LR model using testing subsample$_2$ (2.405) is extremely expensive compared to the EMC associated with the DA model using same subsample (0.172) and the EMC associated with the LR model using testing subsample$_1$ (1.284).

Figure 5.6: Gains charts for testing subsample$_1$ and testing subsample$_2$ using LR





5.7 Comparison of results of various bank FSR group membership models

In this section, the researcher compared the ACC rates of the various models to evaluate the classification capability of the proposed models. Table 5.29 summarises the ACC rate results for machine-learning techniques (CHAID, CART and MLP neural nets) and conventional techniques (DA and LA) using the three different samples [i.e., the entire data set, subsample$_1$ (training and testing) and subsample$_2$ (training and testing)].

Table 5.29 suggests that CHAID has the highest ACC rates (93.6%, 97.4% and 97.4%) among all machine-learning and conventional techniques applied in this thesis using the entire data set, training subsample$_1$ and training subsample$_2$, respectively. However, using testing subsample$_2$, CART has the highest ACC rate (92.2%). For testing subsample$_2$, the highest ACC rate is associated with DA (92.2%). All machine-learning techniques predict low FSRs better than high FSRs using the entire data set, except one model (i.e., CHAID). On the other hand, both conventional techniques (i.e., DA and LR) predict high FSRs better than they do low FSRs using the entire data set.

Table 5.29: Comparing classification results for various techniques

Bank FSR Group Membership Model	Classification Results		
	High FSR %	Low FSR %	Overall %
CHAID			
Entire data set*	96.5	96.1	96.3
Subsample$_1$			
Training **	96.5	98.7	97.4
Testing	82.2	93.1	87.9
Subsample$_2$			
Training****	95.2	99.2	97.4
Testing	91	85.7	88.8
CART			
Entire data set	94.8	96.1	95.4
Subsample$_1$			
Training	97.4	96.7	97
Testing ***	89.7	94.8	92.2
Subsample$_2$			
Training	97.1	96.9	97
Testing	83.1	83.7	82.8
MLP neural nets			
Entire data set	91.9	96.1	94
Subsample$_1$			
Training	96.4	91.7	94
Testing	91.4	81	86.2
Subsample$_2$			
Training	95.2	94.6	94.9
Testing	80.6	81.6	81
DA			
Entire data set	96.5	90	93.2
Subsample$_1$			
Training	97.4	90.9	94
Testing	94.8	77.6	86.2
Subsample$_2$			
Training	99	89.2	93.6
Testing*****	88.1	98	92.2
LR			
Entire data set	81.4	65.9	73.5
Subsample$_1$			
Training	97.4	81.8	89.3
Testing	91.4	79.3	85.3
Subsample$_2$			
Training	74.3	53.1	62.6
Testing	23.9	61.2	39.7

Source: Developed by the researcher (based on the statistical output).

Note. * Best of all technique using entire data set; ** Best of all techniques using training subsample$_{1;}$ *** Best of all techniques using testing subsample$_{1;}$ **** Best of all techniques using training subsample$_{2;}$ ***** Best of all techniques using testing subsample$_{2.}$

In line with this, the researcher compared the various models' EMCs to evaluate the overall effectiveness of the techniques and to find the minimum estimated misclassification cost for the proposed models. Table 5.30 summarises the Type I and II errors and the EMC for all proposed models in this study.

Table 5.30: Errors and estimated misclassification costs for all proposed models

Bank FSR group membership models	Entire data-set			Training subsample$_1$			Testing subsample$_1$			Training subsample$_2$			Testing subsample$_2$		
	Error results		EMC	Error results		EMC	Error results		EMC	Error results		EMC	Error results		EMC
	Type I	Type II		Type I	Type II		Type I	Type II		Type I	Type II		Type I	Type II	
CHAID	0.035	0.039	0.256	0.035	0.017	0.119	0.172	0.069	0.5	0.048	0.008	0.072	0.09	0.143	0.776
CART	0.052	0.039	0.265	0.026	0.033	0.217	0.103	0.052	0.362	0.029	0.031	0.217	0.179	0.163	0.931
MLP neural nets	0.081	0.039	0.279	0.036	0.083	0.528	0.086	0.19	1.181	0.048	0.054	0.379	0.194	0.184	1.04
DA	0.035	0.10	0.632	0.026	0.091	0.574	0.052	0.224	1.37	0.01	0.107	0.719	0.119	0.02	0.172
LR	0.186	0.341	2.177	0.026	0.182	1.136	0.086	0.207	1.284	0.257	0.469	3.23	0.761	0.388	2.405

Source: Developed by the researcher (based on the statistical output).
Note. The ratio of EMC associated with Type I and Type II errors provides a sensitivity analysis using cost ratio at 1:12. This high cost ratio is mainly a result of the high political risk of countries in the Middle East region.

Table 5.30 reports that CART, MLP neural nets, DA and LR predict low FSRs much better than high FSRs using the entire data set. This is mainly because Type I errors of these four techniques are higher than Type II errors. In contrast, CHAID predicts high FSRs better than it does low FSRs as Type I errors are smaller than Type II error. Additionally, Table 5.30 reveals that the three machine-learning technique (i.e., CHAID, CART and MLP neural nets) have lower EMCs than do the conventional techniques (i.e., DA and LR) using the entire data set.

Furthermore, the results show that CHAID has the lowest EMC at 0.256 across all proposed models (conventional and machine-learning techniques) using the entire data set, as the Type I error rate is the lowest compared to other machine-learning techniques (i.e., CART and MLP neural nets). This supported by the fact that the ACC rate criterion also resulted in selection of CHAID at 96.3% using the entire data set (see Table 5.29).

For training subsample$_1$, the Type II error rates exceed Type I error rates, as in the case of CART, MLP neural nets, DA and LR. Correspondingly, the Type I error rate surpasses the Type II error rate only in the case of CHAID .The lowest misclassification cost is 0.119 for CHAID across all proposed models using training subsample$_1$. It is worth mentioning that CHAID has the highest ACC rate at 97.4% using training subsample$_1$ (see Table 5.29). This is not the case for testing subsample$_1$, for which Type I error rates outstrip Type II error rates, as in the case of CHAID and CART; the lowest EMC is 0.362 for CART across all proposed models. This is confirmed by the highest ACC rate at 92.2% associated with CART using testing subsample$_1$ (see Table 5.29). Furthermore, where the Type II error rates exceed the Type I error rates, as for MLP neural nets, DA and LR; the lowest EMC is 1.181 for MLP neural nets.

For training subsample$_2$, CHAID's Type I error is higher than its Type II error with the lowest EMC at 0.072 across all proposed models. Again, CHAID has the highest ACC rate at 97.4% using training subsample$_2$ (see Table 5.29). On the other hand, Type II error rates exceed Type I error rates, as for CART, MLP neural nets, DA and LR. Finally, CHAID's Type II error rate exceeds its Type I error rate with EMC at 0.776 using testing subsample$_2$. In contrast, Type I error rates are higher than Type II error rates, as for CART, MLP neural nets, DA and LR; surprisingly, the lowest EMC is 0.172 for DA across all proposed models using testing subsample$_2$ because of a minimal Type II error rate (see Table 5.30). In line with this, the highest ACC rate in this case is for DA at 92.2% (see Table 5.29).

5.8 Conclusion

In the last few decades, evaluations of the creditworthiness of banks have become very challenging because of the opaqueness of the banking sector and the high variability in creditworthiness. The recent financial crisis has provided indications that (1) the banking system faces severe problems across different regions, and (2) an effective prediction of the correct bank FSR group memberships is becoming a necessity. This chapter presents practical knowledge to bank managers in the Middle East region regarding the use of publicly available data (i.e., financial and nonfinancial variables) to predict bank FSR group membership. The well-known methods of estimation employed in this chapter are machine-learning techniques (i.e., CHAID, CART and MLP neural nets) and conventional techniques (i.e., DA and LR).

The ranking of the models varies according to the sample considered in the sub-runs. When the entire data set, training subsample$_1$ and training subsample$_2$ are considered, CHAID is preferred in terms of its association with the highest ACC rate and the lowest EMC across all proposed models. As for testing subsample$_1$, CART is associated with the highest ACC rate and the lowest EMC. The results also reveal that DA is the best model using testing subsample$_2$ as it is associated with the highest ACC rate and lowest EMC because of a minimal Type II error rate.

In general, the researcher concludes that machine-learning techniques (i.e., CHAID, CART and MLP neural nets) are superior to conventional techniques (DA and LR) in terms of predicting correct bank FSR group memberships in the Middle East region. Interestingly, in terms of DA, the researcher also concludes that the relative contribution of financial variables

(65.5%) is higher than that of nonfinancial variables (34.5%) in the discriminatory function. Accordingly, bank managers must give relatively higher weight to financial over nonfinancial variables when formulating bank policies and strategies that promote banks' high FSRs.

CHAPTER 6 CONCLUSION

6.1 Introduction

Massive interest over recent decades has been turned toward the relationships between bank financial and nonfinancial performance measures and FSRs. RAs stress that their ratings are based on opinions about the overall creditworthiness of the obligor (e.g., sovereign, corporate or bank) regarding its ability to fulfil its financial obligations. Specifically, bank rating is conventionally conducted by external RAs who follow opaque and unpublished methods to assign ratings based on banks' financial and nonfinancial variables. Therefore, a lack of consensus is observed regarding the ability of RAs to assign correct bank ratings. Bank FSRs are ordinal measures that send signals to market participants about banks' current and future financial positions and their default probability. Bank FSRs have become essential especially after the recent financial turmoil.

Additionally, bank FSRs play a crucial role in relation to the creditworthiness of the financial system in the Middle East. A strong bank FSR assists the bank in accessing capital markets in better condition and positively affects bank operations and performance. However, RAs face difficulties in developing an accurate rating system for banks because of the opacity of and the leverage across financial institutions. This understanding is supported by the fact the three major RAs (i.e., Moody's, Standard & Poor's and Fitch) disagree more highly when issuing bank ratings than when issuing ratings for corporations and countries (Cantor and Packer, 1994; Hammer et al., 2012; Moon and Stotsky, 1993; Morgan, 2002). Some studies have concluded that the opacity of rating processes has resulted in, among other issues, the housing bubble and consequently the financial crash of 2007-08 (Bussani, 2010; Diomande et al., 2009).

The relevant literature on bank FSRs also includes an intermediary factor that is bank CS. The reason for the involvement of bank CS is that it affects bank FSRs given that the adjustment of bank CS is largely controlled by bank supervisory regulations (e.g., Basel I, II and III). These regulations have a universal objective, which is to protect bank capital by using classified guidance for bank asset quality, capital adequacy, credit risk, liquidity and profitability. Therefore, because the sources of bank capital are regulated, bank FSRs are implicitly regulated. This understanding requires bank managers to design financial strategies that do not deviate from regulations and promote the bank to a high- or near-high FSR.

The next question that occurs is why one needs to know about bank FSRs specifically in the Middle East region. The literature on the determinants and prediction of bank ratings is extensive and well established in the developed economies (Belloti et al., 2011a; Hammer et al., 2012; Öğüt et al., 2012; Pasiouras et al., 2006; Poon et al., 1999; Poon and Firth, 2005). It is worth mentioning that the examination and prediction of bank FSR group membership issued by CI is not addressed in the relevant studies in either developed or developing economies.

For the Middle East region, the researcher summarised banking sector problems as follows: (1) Middle Eastern banks' equity financing has been obtained mainly from governments; (2) because most Middle East banks were government banks, there was less need to assess banks' creditworthiness (Harington, 1997). Governments use their banks to finance their economic activities to an extent that has caused a disconnection between bank FSR and bank CS; (3) The market forces that monitor capital risk were absent as the stock markets were underdeveloped or even non-existent in many Middle East countries (Godlewski, 2007). This situation has led to less interest in bank FSRs (47.4% of commercial banks—64 out of 135—are rated); and (4) the opening and development of various stock markets in the region has encouraged many foreign banks to establish businesses in the region, which has driven the mostly unrated Middle East banks to performance comparable to that of rated foreign banks.

Given the above problems, it was important to examine the impact of bank CS decisions on the assignment of bank FSRs. It was equally important to investigate the association between bank FSRs and bank performance in terms of financial and nonfinancial variables. To achieve this, the ML technique is used to determine the main financial and nonfinancial variables associated with high- and near-high FSRs versus low- and near-low FSRs of active commercial banks in the Middle East region. In addition, this thesis identified how bank managers and investors in the Middle East region can use publicly available financial and nonfinancial data to discriminate between bank FSR group memberships (i.e., high- versus low-FSRs).

This thesis predicted bank FSR group memberships using machine-learning techniques (i.e., CHAID, CART and MLP neural nets) and conventional techniques (DA and LR). The reason for the use of those statistical techniques is to examine whether various results in terms of ACC rates, EMCs and gains charts are achieved; to investigate the effect of different sizes of data sets [i.e., the entire data set (351 observations), $subsample_1$ (67% training, 235 observations and 33% testing, 116 observations) and $subsample_2$ (2001-2006 training, 235 observations and 2007-2009 testing, 116 observations)] on the ACC rates and EMCs ; and to provide practitioners and researchers with a wide range of bank FSR group membership models by which to evaluate the predictive ability of various statistical predictive techniques. The analysis and the results are further discussed in this chapter, which summarises the research findings.

To the best of the researcher's knowledge, no other studies in the banking sector in the Middle East region have been conducted using conventional and machine-learning techniques to predict bank FSR group memberships. Therefore, the current thesis can help bank managers understand the intrinsic process used by the analysts of an RA when assigning bank FSRs. The main objective is to develop strategies that help improve banks' FSRs.

6.2 Summary of research findings

The results of the financial and nonfinancial characteristics of bank FSRs in the Middle East region suggest the conclusions that follow.

6.2.1 Summary of ML findings

In this section, the researcher summarises the ML results starting by the bank performance financial categories separately and then followed by all financial categories.

6.2.1.1 Bank performance financial categories

For the asset quality category, low- and near-low-FSR banks in the Middle East are characterised by selling loans (mostly uncollateralised) according to governmental directions. This situation has resulted in an accumulation of mostly nonperforming loans over the years. On the contrary, high- and near-high-FSR banks are more conservative about selling loans. This argument is supported by the evidence that the average rate of ILGL for low- and near-low-FSR banks (14%) is much higher than that for high- and near-high-FSR banks (4%).

The observed evidence is that low- and near-low-FSR banks in the Middle East do not accumulate adequate balances of loan loss reserves to compensate for increases in nonperforming loans. Consequently, investor confidence about bank asset quality deteriorates and bank FSRs assigned by RAs are negatively affected. This result is supported by the fact that average rate of LLRIL for high- and near-high-FSR banks (139%) is higher than for low- and near-low-FSR banks (90.4%).

In addition, low-FSR banks accept highly risky loans without proper remuneration in terms of margins. Accordingly, bank asset quality deteriorates, which negatively affects the bank's FSR. This finding is intuitive and consistent with Van-Roy (2006) and Pasiouras et al. (2006) for the developed economies. On the contrary, high- and near-high-FSR banks in the Middle East are well-run banks in terms of compensating highly risky loans with greater interest margins. This argument is supported by the fact that average rate of LLPNIR for low- and near-low-FSR banks (26.7%) is higher than the same average for high- and near-high-FSR banks (17.4%). Finally, it is worth noting that because the two models (e.g., Model 1 and Model 2) are significant at 99% confidence level, the alternative hypothesis (H_{A2}) is not rejected.

As for capital adequacy results, low- and near-low-FSR banks in the Middle East are undercapitalised and high- and near-high-FSR banks are well capitalised. This debate is supported by the fact that the average rate of CS ratio associated with high- and near-high-FSR banks (12.5%) is higher than the same average rate associated with low- and near-low-FSR banks (10.9%). This finding is in line with results reported by Pasiouras et al. (2006, 2007), Belloti et al. (2011a) and Chen (2012).

Additionally, low-FSR banks are selling more loans (although mostly nonperforming) without remuneration in terms of available equity. Conversely, it seems that managers of high-FSR banks are firm and strict about maintaining the appropriate amount of equity cushion to absorb expected losses on their loan book. This finding validates results reported by Poon et al. (2009).

Moreover, the researcher noted that managers of low- and near-low-FSR banks in the Middle East are not capable of mitigating high risk weighted assets by increasing Tier 1 and Tier 2 bank capital. On the contrary, high- and near-high-FSR banks maintain an adequate level of TCR to satisfy Basel I and II requirements. This debate is supported by the fact that the average rate of TCR associated with high- and near-high-FSR banks (20.8%) is higher than the average rate of TCR associated with low- and near-low-FSR banks (10%).

Finally, the researcher concludes for the capital adequacy category that Middle East banks rely more on debt (i.e., deposits) rather than equity to finance their assets regardless of the assigned FSR. This finding is intrinsic to the Middle East banking industry in light of the historical evolvement of the banking industry, which arose from governmental funds. Specifically, the contribution of public equity has emerged recently according to openings and the pace of progress of stock markets in the region. Finally, the two models of the capital adequacy category are significant at the 1% level, which indicates that the alternative hypothesis (H_{A3}) outperforms the null hypothesis (H_{03}).

The empirical results revealed that banks in the Middle East have certain credit risk characteristics summarised as follows: (1) low-FSR banks have poor quality loan portfolios and near-high-FSR banks have better quality loan portfolios because they adopt firm management strategies and policies regarding the issuance of corporate and retail loans. This argument is supported by the fact that the average rate of loan loss reserve to gross loans ratio (LLRGL) for low-FSR banks (14.27%) is higher than same average for high-FSR banks (3.65%). Finally, this result supports the validity of the ILGL ratio result under the asset quality category.

Further, high-FSR banks are more conservative and rational regarding expected loan losses and build a capital buffer against expected loan losses that are written off against banks. In line with banking activity, high-FSR banks are willing to maintain their good reputations and depositors' confidence levels by reducing their probability of failure by applying defensive or firm techniques to guide the issuance of corporate and retail loans. This argument is supported by the fact that the average rate of loan loss reserve to equity ratio (LLRE) for high-FSR banks (22.9%) is somewhat lower than the average rate of LLRE for low-FSR banks (62.3%).

In addition, low-FSR banks employ poor credit management techniques, which forces banks to increase balances of annual provision to alleviate expected future losses that may arise from poor quality loan portfolios. On the contrary, high- and near-high-FSR banks implement firm credit management techniques that result in lower annual provisions than for low-FSR banks. This argument is supported by the fact that average rate of LLPTL for low- and near-low-FSR banks (1.47%) is higher than that for high-and near-high-FSR banks (0.73%). This finding confirms results reported for the LLRGL ratio.

Finally, results for the loan loss provision to equity ratio (LLPE) confirm that low-FSR banks do not accumulate an appropriate amount of capital cushion to lessen high credit risk exposure. However, high-FSR banks confirm an opposite scenario because of the implementation of firm credit management techniques, which ultimately result in better credit decisions and reduce credit risk exposure. This debate is confirmed by the fact that average rate of LLPE ratio for low-FSR banks (9.4%) is slightly higher than the average rate for high-FSR banks (8.35%). In conclusion, the two models of the credit risk category are significant at the 99% confidence level, which indicates that the null hypothesis (H_{04}) is rejected in favour of the alternative hypothesis (H_{A4}).

Concerning the liquidity position of banks in the Middle East, the following elucidates the main characteristics of bank liquidity positions associated with various FSRs. It seems that low-FSR banks sell larger amounts of poor quality loans, which results in a higher degree of liquidity risk exposure and inversely affects FSR assignment. On the other hand, it appears that high- and near-high-FSR banks do not depend entirely on selling loans as their main source of revenue. However, they invest in other financial activities and instruments to maintain safe liquidity positions and thus obtain high- or near-high-FSRs.

In line with this, it appears that high- and near-high-FSR banks invest more in liquid assets to maintain good liquidity positions to withstand sudden withdrawal of customers and short-term funding. It should be noted that high-FSR banks prefer excess liquidity to fund the growth in the retail market and to finance the booming small-medium size corporate sector in the Middle East region. In general, these two areas are considered huge opportunities for the potential growth of the banking industry in the Middle East region. On the other hand, it appears that low- and near-low-FSR banks do not maintain an appropriate amount of liquid assets and thus obtain low FSRs. This is supported by the fact that the average rate of liquid asset to deposit and short-term funding ratio (LADSTF) for high- and near-high-FSR banks (41.6%) is greater than average rate for low- and near-low-FSR banks (33.1%). As a final point, the two models of the liquidity category are significant at the 1% level, which shows that the alternative hypothesis (H_{A5}) is not rejected.

The empirical results provide clear evidence that bank profitability in the Middle East region is a strong determinant of bank FSR assignment. This is supported by the fact that the profitability category has the highest explanatory power of all of the categories. Also, the researcher concludes that bank management capabilities and characteristics have a great impact on FSR assignment. Banks' managers that are unable to use security gains or losses and other tax-management tools (such as the purchase of tax-exempt bonds) to minimise banks' tax exposure usually acquire low- and near-low-FSR. However, high- and near-high-

FSR banks' managers are proficient and experienced in terms of using new financial instruments or techniques to reduce bank tax exposure. This argument is supported by the fact that average rate of tax management efficiency (TME) for low- and near-low-FSR banks (80.5%) is somewhat lower than the average rate for high- and near-high-FSR banks (97.1%).

Furthermore, low- and near-low-FSR banks manage cost-side activities inefficiently relative to the generated income side; whereas near-high-FSR banks operate at low cost. This finding is consistent with the new era of the banking industry, which focuses on movement toward automation and installation of sophisticated electronic systems instead of older, labour-based production and delivery systems. This reduces bank overhead costs relative to generated income. It is worth mentioning that the average rate of cost-to-income ratio (CIR) for low- and near-low-FSR banks (46.5%) is higher than the average rate for high- and near-high-FSR banks (34.6%).

Moreover, low- and near-low-FSR banks do not efficiently utilise their available assets (i.e., loans, investment securities and fees earned from fiduciary activities) to generate an appropriate amount of total operating revenue (interest and noninterest). On the contrary, high- and near-high-FSR banks implement effective asset portfolio management policies. It should be noted that the average rate of asset utilisation (AU) for low- and near-low-FSR banks (6.2%) is slightly lower than the average rate for high- and near-high-FSR banks (7.3%).

In addition, low- and near-low-FSR banks in the Middle East make unprofitable operating decisions and thus these banks reduce the spread between interest revenue generated by earning assets and interest expense paid to interest-bearing liabilities. On the other hand, high- and near-high-FSR banks are proficient and qualified in generating the maximum amount of revenue by using the cheapest sources of funding. Additionally, this argument is supported by the fact that the average rate of net interest margins (NIM) for high- and near-high-FSR banks (3.2%) is slightly higher than average rate for low- and near-low-FSR banks (3.0%).

Further, low-FSR banks either suffer from expense-control problems or decreasing revenues. This erodes net income, which negatively affects the rate of return on funds invested by stockholders of low-FSR banks. Along with this, it seems that low-FSR banks ineptly use their assets to generate an appropriate amount of income even after adding the provision for loan losses. On the other hand, high- and near-high-FSR banks employ efficient banking operation techniques and strategies that result in superior shareholder returns. This debate is confirmed by the fact that average rate of return on average equity (ROAE) for low- and near-low-FSR banks (15.4%) is somewhat lower than the average rate for high- and near-high-FSR banks (17.8%).

Additionally, low- and near-low-FSR banks are unable to control bank operating expenses efficiently. On the contrary, high- and near-high-FSR banks maintain better control over their operating expenses as these banks are more enthusiastic about advances in automation and mergers. Accordingly, this eliminates many overlapping facilities and thus reduces overhead and operating expenses. It is also worth mentioning that the average rate of the expense control efficiency ratio (ECE) for high- and near-high-FSR banks (34.5%) is higher than the average rate for low- and near-low-FSR banks (27%). In conclusion, the two models of the profitability category are significant at the 99% confidence level, which indicates that the null hypothesis (H_{06}) is rejected in favour of the alternative hypothesis (H_{A6}).

6.2.1.2 All financial categories

The researcher ran ML regressions for all financial categories to validate the results reported earlier under the five bank performance categories and to examine the overall explanatory power for bank FSR.

6.2.1.2.1 Financial variables

The researcher concludes that the asset quality measure (i.e., LLRIL) is an essential financial measure for CI for assignment of high- and near-high- FSRs. For capital adequacy, it seems that banks' that wish to attain high- or near-high FSRs must pay more attention to capital adequacy measures (i.e., CS, TCR and EM). Note that CS is significant across all 12 models in this thesis, which prompts not rejecting the alternative hypothesis (H_{A1}).

Further, this thesis confirms the significance of banks' credit risk measures (i.e., LLRGL and LLPTL ratios) for CI to assign banks in the Middle East a high- or near-high FSR. Another piece of information that is derived from this thesis is that the management of liquidity measures (i.e., LR) is an essential financial measure for banks that seek high- or near-high-FSRs. Finally, profitability measures (TME, ECE, AU, CIR and NIEAA) are the most important measures employed by CI to assign banks in the Middle East high- or near-high FSRs.

6.2.1.2.2 Nonfinancial variables

The researcher concludes that banks operating in countries in the Middle East that have low sovereign ratings are assigned low- and near-low FSRs. On the other hand, banks operating in countries with high sovereign ratings are assigned high- and near-high FSRs. This confirms that CI identifies the impact of macroeconomic variables and the surrounding environment on the overall performance of banks, which eventually affects their FSRs. This finding is intuitive and consistent with results reported by Poon and Firth (2005), Van-Roy (2006), Poon et al. (2009) and Belloti et al. (2011a). It should be noted that SR is significant across all six models, which prompts not rejecting the alternative hypothesis (H_{A7}). Size was significant across five of the six models, and so it is likely to have a significant effect on CI decisions in the bank-rating process. The time variable was only significant in three of the models, and so it had some influence but was not as important as the size effect. Regarding the country variable, it had been dropped because of high correlation with SR and its possible inclusion under alternative models had been associated with quite good, yet inferior, models in terms of pseudo R-square. This suggests that, although the country effect has relevance, SR is a better guide for CI decisions in the bank-rating process than the country effect *per se*.

6.2.2 Summary of bank FSR group membership results

This thesis concludes from DA results that financial variables are associated with higher discriminatory power than nonfinancial variables, which prompts not rejecting the alternative hypothesis (H_{A11}). Thus, bank managers must give relatively higher weight to financial rather than nonfinancial variables when formulating bank policies and strategies to promote high FSRs for banks. This is validated by the DA findings, which state that all financial variables (LLPNIR, ILGL, TCR, CS, ENL, REP, AU and LLPTL) contribute to the model's discriminatory power by 65.5%, and nonfinancial variables (size, SR and T) contribute to the model's discriminatory power by 34.5%.

The empirical results reveal that CI depends heavily on the following three aspects to assign bank FSRs in the Middle East: (1) the extent to which the banks utilise their available assets efficiently; (2) the extent to which banks use leverage to finance their lending activities and (3) the quality of banks' loan portfolios. Additionally, the results imply that CI assigns relatively more weight to bank size and country SR than other non-financial determinants in the process of FSR assignment in the Middle East.

In terms of financial variables, the DA results prompt the conclusion that high-FSR banks are differentiated from low-FSR banks in terms of their being well capitalised. The positive sign associated with the coefficients of the capital adequacy proxies (i.e., CS, TCR and ENL) confirm this. The empirical results also reveal that high-FSR banks more efficiently utilise their assets and generate an appropriate amount of income even after adding back provisions for loan losses from their available assets than do low-FSR banks. This is emphasised by the positive sign associated the coefficients of the profitability proxies (AU and REP). Additionally, high-FSR banks are characterised by the use of robust credit-management techniques, thus attain better loan portfolio quality; in addition, they compensate highly risky loans with greater interest margins. The negative sign associated with the coefficients of LLPTL, LLPNIR and ILGL assert this.

Regarding nonfinancial variables, the findings indicate that countries' economic and financial conditions play a vital role in the process of FSR assignment by CI. The positive sign associated with the SR coefficient confirms that high-FSR banks operate in countries with stable economic and financial conditions. Furthermore, the results indicate that high-FSR banks are usually large in size, as the size factor is associated with a positive coefficient sign. Finally, the negative sign associated with the coefficient of the time dummy variable implies that FSRs of Middle East banks deteriorated slightly during the period from 2001 to 2009.

In terms of banks' FSR group memberships' prediction, sophisticated machine-learning techniques outperform conventional techniques, which suggest the rejection of the null hypothesis (H_{012}) in favour of the alternative hypothesis (H_{A12}). The ranking of the models varies according to the sample included in the sub-runs. When the entire data set, training subsample$_1$ and training subsample$_2$ are considered, CHAID is preferred in terms of having the highest ACC rate and the lowest EMC across all proposed models in this thesis. For testing subsample$_1$, the highest ACC rate and the lowest EMC rate are associated with CART. The results also show that the DA is the best model using testing subsample$_2$ with the highest ACC rate and the lowest EMC rate because of minimal Type II error rates. In general, it can be concluded that machine-learning techniques (i.e., CHAID, CART and MLP neural nets) are superior to the conventional techniques (i.e., DA and LR) in terms of accurate predictions of bank FSR group memberships in the specific environment chosen (i.e., the Middle East region).

6.3 Policy implications

Bank rating is one of the public economic issues that drive the development of capital market regulations in any country. In this thesis, the researcher has reached many significant results that help economic policy makers in many aspects as follows:

(1) An accurate bank's rating would help determine the bank's creditworthiness, and therefore enable policy makers, especially in the capital markets, to allocate the public funds efficiently. Accordingly, the highly rated banks are worth an allocation of a relatively higher proportion of the public funds that would eventually result in high investment returns to the economy.

(2) Bank ratings play a significant role when it comes to the assessment of bank's efficiency by investors and capital market regulators. Hence, a correct rating indicates how efficiently the bank is being run, which directly reflects the investment worthiness of the bank. In other words, a bank's high rating signals the soundness of its investment strategies that eventually lead to an improvement in the public wealth.

(3) As for financial disclosure, precise bank ratings help capital market regulators disclose the authentic financial information to the public. This is of great

importance as it helps support the universal claims of enhanced financial transparency.

6.4 Research limitations

The analysis in this thesis is subject to number of limitations; however, it should be stressed that these limitations and constraints do not devalue the research outcomes, but rather, indicate the need for additional research to be conducted in this area.

Firstly, the research time frame is 2001-2009 due to bank scope data limitation. Secondly, the sample used includes rated rather than non-rated commercial banks in the Middle East region. Thirdly, banks' FSRs data are based on the CI rating agency. Finally, the prediction analysis outcomes reflect banks' FSR group memberships rather than the prediction of banks' FSRs.

6.5 Recommendations for future research

The above mentioned limitations call for further research as follows:

(1) It has become a necessity to compare the determinants of commercial and Islamic bank FSRs due to the technical and operational characteristics in both types. This research can be enriched taking into account the developed and developing economies.

(2) There must be updates to the findings of the determinants of bank FSRs after 2009. It is worth noting that the global waves of the introduction of Islamic finance must have had significant effects on bank financial performance since 2009 onward.

(3) There are also practical and viable research venues using the conventional and machine learning statistical techniques for predicting bank FSRs. The necessity of this research stems from the fact that the quality of bank FSR predictions serves as

early warning signals of bank performance. The latter is a crucial prerequisite in order to prepare for a protection of bank capital. Furthermore, these prediction techniques provide practical knowledge to bank managers in terms of developing FSRs to the non-rated banks.

(4) The reality of the operations of RAs shows that they differ among each other in terms of the published data. This anomaly calls for a consideration of bank FSRs developed by different RAs. In addition, there is also another type of data, namely bank governance- related data, which show the effects of the quality of governance on bank FSRs.

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Appendix A: Summary of the Relevant Studies in the Literature

Author	Objectives	Methods	Main Results
Poon et al. (1999)	To predict Moody's bank financial strength ratings (BFSR) using bank specific financial data and to include an aggregate measure (between 0 and 100) to measure the economic, political and financial risk in the country in which the bank operates (country effect). In addition, the authors examine the relative importance of information provided by BFSR compared to that contained in traditional debt ratings.	**Dependent variable**: Moody's BFSRs range from A to E+, coded as 10 ordinal values. **Independent variables**: The study starts with 100 financial variables and ratios that cover the major measures of profitability, efficiency, asset composition, interest composition, interest coverage, leverage and interest. Using varimax rotation factor analysis, three financial factors account for more than 50% of the variability in the data set are selected: risk measures, asset management and profitability. Thus, independent variables include bank risk, loan provision ratio, profitability, long-term debt rating, short-term debt rating and country risk. **Sample:** 130 banks from more than 30 countries as of June 1997; financial variables are from 1996. **Methodology**: Ordered logistic regression model	• BFSR provides similar but not identical information to that contained in traditional debt ratings (both long- and short-debt ratings). Thus, BFSR does not have a high supplementary contribution when compared to Moody's traditional ratings. • The effect of country risk on BFSRs is insignificant. This is mainly because of the homogeneity in bank financial disclosures across countries and the maintenance of minimum capital adequacy ratios required by the BIS. • Three financial variables help to classify BFSRs. The loan provision information is the most important financial variable as it is statistically significant across all models. The second most important financial variable is the bank risk variable, whilst profitability is the third most important variable. The inclusion of these three financial variables improves the predictive power of models that include only long-term and short-term debt ratings.

Author	Objectives	Methods	Main Results
Laruccia and Revoltella (2000)	To identify the main determinants of overall banking system soundness and stability and to construct a microeconomic model to predict Moody's BFSRs using different econometric techniques.	**Dependent variable**: Moody's BFSR coded on a 1 (A) to 9 (E) scale **Independent variables**: Long-term bank deposit country ceiling (LTBDCC) as a proxy for country risk, the ratio of loan loss reserve to gross loans and loan loss provision to net interest revenue as proxies for asset quality; the ratio of equity to total assets, log of the total equity, the ratio of equity to net loans, the ratio of equity to customer and short-term funding and the ratio of equity to total liabilities as proxies for bank capitalisation; cost-to-income ratio, net interest margin, the ratio of net interest revenue to average assets, the ratio of other operating income to average assets, the ratio of non-interest expense to average assets, the ratio of non-operating items and taxes to average assets, return on average assets and return on average equity as a proxies for bank profitability; the ratio of net loans to total assets and the ratio of net loans to customer and short-term funding as a proxies for bank liquidity and country dummy variables to highlight structure differences between regions and countries. **Sample:** 212 banks operating in developing and transition economies (38 in East	• The empirical results revealed that neural network model explains 76.7% of the variance of the BFSRs, the linear regression model explains 73.5% and the logistic model explains only 71%. • The findings show that the effect of country risk on BFSRs is highly significant in the models. • All of the financial ratios have the expected sign for sensitivity. Banks with high BFSRs are associated with high equity-to-total asset ratios (well capitalised) and low cost-to-income ratios (high profitability), low net loans–to-total assets ratio (high liquidity) and low loan loss reserve to gross loans ratio (better quality loan portfolio).

		Europe, 106 in Asia and 68 in South America) as of December 1998. **Methodology**: Linear regression model, logistic regression model and neural network model.	
Poon and Firth (2005)	To identify the main differences in the distribution between Fitch's shadow (unsolicited) ratings and non-shadow (solicited) ratings. The paper examined the main financial characteristics associated with Fitch's shadow bank ratings and whether they differ from those associated with Fitch's nonshadow ratings. Finally, the paper buildt a statistical model to recognise differences in bank ratings.	**Dependent variable**: Fitch's Bank Individual Ratings (FBRs) coded on a nine-point ordinal scale [9 (A) to 1(E)]. **Independent variables**: Profitability proxies including net interest margin, the ratio of net interest revenue to average total assets, the ratio of pre-tax operating income to average total assets, return on average assets, return on average equity, dividends payout ratio and cost-to-income ratio. Asset quality proxies including the ratio of loan loss reserve to gross loans, the ratio of loan loss provision to net interest revenue, the ratio of loan loss reserves to nonperforming loans, the ratio of nonperforming loans to gross loans and the ratio of net charge off to net income before loan loss provisions. Liquidity proxies including interbank ratio, the ratio of loans to total assets, the ratio of loans to customer and short-term funding, the ratio of loans to total deposits, the ratio of liquid assets to total deposits and borrowings and the ratio of liquid assets to customer and short-term funding. Capital adequacy proxies including Tier 1 capital	• The empirical results revealed that Fitch's shadow ratings are lower than non-shadow rating. • The results indicate that larger and more profitable banks located in countries with high sovereign credit ratings tend to obtain high FBRs. Banks with high loan loss reserve-to-gross loan ratio (poor asset quality) and high loan-to-total asset ratios (poor liquidity positions) are assigned low FBRs. • The findings indicate that the most significant factors in determining FBRs are bank size, profitability, asset quality, liquidity and sovereign credit risk.

		ratio, capital adequacy ratio, the ratio of equity to total assets, the ratio of equity to total loans and the ratio of equity to customer and short-term funding. Ln total bank assets as a proxy for bank size. Fitch's sovereign credit ratings were coded as 12 ordinal values where AAA = 12 and D = 1. **Sample:** 1,060 banks in 82 countries rated by Fitch as of 2002. **Method**: Heckman's two-step treatment estimation method.	
Pasiouras et al. (2006)	To examine the determinants of FBRs by considering bank regulation and supervision framework, market structure and bank specific characteristics.	**Dependent variable:** FBRs coded on five main categories: A and A/B coded as 4, B and B/C coded as 3, C and C/D coded as 2, D and D/E coded as 1 and E coded as 0. **Independent variables:** Divided into three main groups: *Bank-specific variables* include the ratio of equity to total assets as a proxy for capital strength, the ratio of loan loss provision to net interest revenue as a proxy for asset quality, return on assets as a proxy for profitability, the ratio of cost to income ratio as a proxy for management quality or efficiency, the ratio of liquid assets to customers and short-term funding as a proxy for liquidity, the logarithm of total assets as a proxy for size, the number of subsidiaries as a proxy for diversification of business and franchise power and the number of institutional shareholders as a	• The empirical results revealed that banks with low FBRs are characterised by cost efficiency problems, higher levels of provisions for loan losses compared to their net interest revenue and weaker liquidity positions. On the contrary, banks with high FBRs seem to be more profitable and larger in size. In addition, banks with high equity-to-assets ratios tend to obtain high FBRs only when bank supervision and regulations variables are not included. • Regarding bank regulatory environment, the results indicate that the main determinants of FBRs under all model specifications are capital requirements, restrictions on bank activities, official disciplinary power, explicit deposit insurance scheme, higher deposit insurer

		proxy for bank corporate governance and ownership. *Regulatory and supervisory variables* include 12 variables representing capital requirements, an indication of existence of explicit deposit insurance, power of deposit insurance authority, restrictions on bank activities, accounting and disclosure requirements, auditing requirements, official disciplinary power of the supervisory agency, the ratio of liquidity to diversification index as a proxy for the degree of bank compliance with liquidity and diversification guidelines, entry into banking requirements, limitations on foreign bank entry/ownership, fraction of entry denied and economic freedom index using the Heritage Foundation economic index as a proxy. *Market structure variables* include three variables, the percentage of government-owned banks, the percentage of foreign-owned banks and the degree of asset concentration in the five largest commercial banks. **Sample:** 857banks in 71 countries rated by Fitch as of 2004. **Method:** An ordered logit model**.**	power, liquidity and diversification guidelines, entry requirements, fraction of entries denied and economic freedom. • For market structure variables, the results showed a positive (negative) relationship between the share of assets in foreign owned banks (degree of asset concentration and share of assets in government owned banks) and FBRs. • Banks in developed countries tend to have high FBRs only when bank supervision and regulations variables are not included in the model.

Author	Objectives	Methods	Main Results
Van-Roy (2006)	To examine the whether or not Fitch's treatment of solicited and unsolicited bank ratings are different.	**Dependent variable**: FBRs coded on a scale of 9 (A) to 1 (E). **Independent variables**: A matrix of financial and nonfinancial characteristics that explain the individual rating of banks. *Financial characteristics* include: loan loss provision/net interest revenue as a proxy for risk management, net loans/total assets as a proxy for liquidity, equity/total assets as a proxy for capitalisation, return on assets as a proxy for profitability. *Nonfinancial characteristics* include: banking and finance score estimated by the Heritage Foundation as a for proxy market environment, log (total assets) as a proxy for diversification/franchise, bank ownership and state ownership as proxies for corporate governance and disclosure index as a proxy for public disclosure. The dummy variable equals 1 if the bank has requested an individual rating and 0 otherwise as a proxy to measure the so-called treatment effect. **Sample:** 169 banks located in 11 Asian countries with both Fitch's solicited and unsolicited ratings as of January 31, 2004. **Methodology**: OLS regression model and endogenous switching regression model.	• The ratios of loan loss provision to net interest revenue and the ratio of net loans to total assets (disclosure index and return on assets) have a statistically significantly negative (positive) impact on individual ratings. • Financial and nonfinancial characteristics are not the main reason for the difference in treatment between solicited and unsolicited rating. However, unsolicited ratings tend to be lower as they are based mainly on public information.

Author	Objectives	Methods	Main Results
Godlewski (2007)	To examine coherence between bank default probabilities and Moody's and Fitch's bank ratings using a scoring and mapping technique applied to banks located in emerging market economies and identifying the main determinants of bank ratings.	**Dependent variable**: Bank default probability, Moody's BFSRs and FBRs **Independent variables**: the Ratio of equity to total loans as proxy for capital adequacy, the ratio of personal expenses to total operating expenses as proxy for bank management, net interest margin as proxy for profitability, the ratio of loan loss reserve to nonperforming loans as proxy for portfolio quality, the ratio of liquid assets to total assets and the ratio of total deposits to total assets as proxies for liquidity. **Sample:** Two samples of 483 and 257 banks for Moody's and Fitch respectively, located in emerging market economies (e.g., South-East Asia, South America and Central and Eastern Europe) during the period from 1998 to 2002. In both samples, The numbers of defaulted banks are were 68 and 48 banks for Moody's and Fitch, respectively. **Methodology**: Logistic regression model.	• For the bank default logit model for the Moody's BFSR sample, the results revealed that profitable, highly liquid and well-capitalised banks with high reserves to cover nonperforming loans tend to have a low bank default probability and thus obtain high Moody's BFSR. • Using the FBR sample, the empirical results revealed that banks with better capital adequacy, more total deposits to total assets and a better cover of nonperforming loan with reserves results in lower bank default probability and thus higher FBRs. • Using a simple scoring model, the results showed coherence between these ratings and actual bank default rates and the mapping results indicated that ratings tend to aggregate bank default probability information into an intermediate low category grade.

Author	Objectives	Methods	Main Results
Pasiouras et al. (2007)	To examine the possibility of predicting FBRs for Asian banks using publicly available data.	**Dependent variable:** FBRs coded on five main categories from A to E. **Independent variable:** *Financial variables:* Total capital ratio, ratio of equity to total assets, ratio of equity to total loans, ratio of equity to customer and short-term funding and the ratio of capital funds to customer and short-term funding as proxies for capital strength. Net interest margin, ratio of net interest revenue to average assets, ratio of other operating income to average assets, return on average assets, return on average equity and recurring earning power as proxies for profit efficiency. The ratio of net interest expense to average assets and the cost-to-income ratio as proxies for cost efficiency. Ratios of net loans to total assets, net loans to customer and short-term funding, net loans to total deposit and borrowings, liquid assets to customer and short-term funding and liquid assets to total deposits and borrowings as proxies for liquidity. Log of total asset as proxy for bank size. Using factor analysis, only five financial variables were selected: ratio of equity to customer and short-term funding as a proxy for capital strength, net interest margin and return on average equity as proxies for	• For financial variables, ratio of equity to customer and short-term funding, net interest margin and return on average equity are the most important financial variables for FBRs. The empirical results revealed that banks with high ratios of equity to customer and short-term funding, return on equity and net interest margin tend to obtain higher FBRs. Thus, profitable and well-capitalised banks are assigned high FBRs. • For nonfinancial variables, the number of institutional shareholders, the number of subsidiaries and the Heritage banking and finance score are the most important for FBRs. A piece of information derived from this study is that regulatory restrictions on bank activity have a negative and significant effect on FBRs, which is consistent with Pasiouras et al. (2006). In line with this, the analysis also revealed that FBRs are significantly positively affected by the number of institutional shareholders and subsidiaries. • The empirical results revealed that MHDIS predicts FBRs with satisfactory classification accuracy (66.03%) compared to discriminant analysis

		profit efficiency, liquid assets to total deposit and borrowings and net loans to total deposit and borrowings as a proxies for liquidity. *Nonfinancial variables*: The auditor's opinion of the bank's financial statements, number of subsidiaries as a proxy for the diversification of business and franchise, number of institutional shareholders, the Heritage bank and finance score to measure the relative openness of a country's banking and financial system and whether or not the bank is listed in the stock exchange. **Sample:** 153 commercial banks located mainly in South and South-East Asian countries as of October 2004. **Method:** Multigroup hierarchical discrimination (MHDIS), discriminant analysis and ordered logistic regression.	(53.73%) and ordered logistic regression (47.55%).
Poon et al. (2009)	To examine whether solicitation matters in bank credit ratings and to identify how and why solicited and unsolicited bank ratings may differ in terms of (1) the main financial characteristics that differentiate between these two rating groups, (2) the potential self-selection bias in which only banks with strong	**Dependent variable**: S&P's long-term credit rating in local currency ranging from AAA to SD/D coded as nine ordinal values (from 9 to 1, respectively). **Independent variables**: *Financial variables* included net interest margin, ratio of net interest revenue to average total assets, pretax operating income to average total assets, return on assets, return on average equity, dividend payout, the ratio of cost to income as proxies for	• Unsolicited bank ratings appear to be usually lower than solicited bank ratings. • Larger banks seek international markets and thus ask S&P's for bank ratings. • Country sovereign risk rating, bank profitability and bank size are important factors in determining bank ratings. • Return on assets (ratio of loan loss reserves to gross loans) is statistically and positively (negatively) significant to S&P's long-term rating.

	financial positions seek ratings and those with poor performance measures do not ask for ratings and (3) the relative importance of each factor in determining bank ratings.	profitability; the ratio of loan loss reserve to gross loans, loan loss provisions to net interest revenue, loan loss reserves to nonperforming loans, nonperforming loans to gross loans, net charge offs to average gross loans and the ratio of net charge off to net income before loan loss provisions as proxies for asset quality; interbank ratio, ratios of loan to total assets, loans to customer and short-term funding, loans to total deposit and borrowings, liquid assets to customer and short-term funding and liquid assets to total deposits and borrowings as proxies for liquidity; Tier 1 capital ratio, capital adequacy ratio, the ratio of equity to total assets, the ratio of equity to loans and equity to customer and short-term funding as proxies for capital adequacy. *Nonfinancial variables* included proportion of solicited ratings of the bank's home country, logarithm of book value of total assets as a proxy for bank size, the book value of trading securities as a proxy for the uniqueness of bank assets, S&P's sovereign credit ratings as a proxy for some important macroeconomic and institutional characteristics of the countries in which the bank operates, a dummy for the number of overseas exchanges on which the bank was listed and a dummy for the number of overseas subsidiaries held by the bank as	• Thus, large and profitable banks with relatively low nonperforming loans to gross loans ratios located in countries with high SRs tend to obtain higher S&P long-term ratings. • Solicitations matter in bank ratings. The impact of solicitation on bank rating is much more significant than that caused by differences in financial profiles.

		proxies for measuring the size and volume of bank international operation. **Sample:** Time-series cross-sectional data for 460 commercial banks in 72 countries, excluding United States, that have solicited and unsolicited credit ratings issued by S&P's from 1998 to 2003. **Method**: Endogenous switching regression model.	
Belloti et al. (2011a)	To identify the impact of financial variables and country risk on predictions of individual bank ratings issued by Fitch.	**Dependent variable:** Fitch's FBRs coded on eight rating categories (A/B, B, B/C, C, C/D, D, D/E and E) where A/B = 8 and E = 1; there were no data on banks with A ratings in this sample. **Independent variables**: Ratio of equity to total assets, liquid assets to total assets, the natural logarithm of total assets, the net interest margin, the ratio of net operating income to total assets, operating expense to total operating income and the return on equity. A time dummy variable and country indicator variables were included to capture country-specific variations in ratings. **Sample:** 681 international banks' ratings between 2000 and 2007 from 90 countries (360 observations). **Method:** Ordered choice estimation techniques and support vector machine.	• Large size (in assets), well capitalised (the ratio of equity to total assets) and profitable (return on equity) banks operating in more stable, developed and rich countries tend to obtain higher ratings. • Banks with high liquidity levels over the previous two periods prior to the rating tend to have a higher bank rating. • On the contrary, lower bank ratings are assigned to banks with a high ratio of operating expense to total operating income. Empirical results revealed recently rated banks tended to obtain lower bank ratings. • Inclusion of country effect enhances the predictive performance of both the ordered choice model and support vector machine. • Results revealed the in-sample predictive accuracy of the support vector machine is substantially better than ordered choice models.

Author	Objectives	Methods	Main Results
Chen (2012)	To classify credit ratings in the Asian banking industry using hybrid procedures and to identify the main determinants of bank credit ratings using an integrated feature-selection approach. This approach formulates a set of rules and regulations that guide the performance of Asian bank mangers, investors and other stakeholders.	**Dependent variable**: Fitch international long-term credit rating for banks for five categories (AA, A, BBB, BB, and B). **Independent variables**: Net interest margin, ratio of net interest revenue to average total assets, other operating income to average total assets, non-interest expense to average assets, recurring earning power, return on average equity, return on average assets and ratio of cost to income as proxies for operation; the ratio of loan loss reserve to gross loans as a proxy for asset quality; the ratios of net loan to total assets, net loans to customer and short-term funding, net loans to total deposit and borrowings, liquid assets to customer and short-term funding and liquid assets to total deposits and borrowings as proxies for liquidity; the ratios of equity to total assets, equity to liabilities and equity to customer and short-term funding as proxies for capital strength, the logarithm of total assets as a proxy for bank size. Using the feature-selection technique, the ratio of liquid assets to customer and short-term funding and the cost to income ratio were eliminated. **Sample:** 1327 Asian banks from 17 Asian countries that have long-term credit ratings issued by Fitch covering the period from	• The proposed procedure in this study outperforms other methods (decision tree-C4.5, Bayes net, OneR, artificial neural networks-multilayer perceptron, logistic and support vector machines using sequential minimal optimisation) with overall classification accuracy rate of 83.84%. • Banks with AA ratings are superior in bank operations (profitability), liquidity and capital strength. • Banks with high levels of liquid assets are assigned high bank ratings. • Banks with BBB ratings are relatively worse in terms of operating, liquidity and capital strength than banks with AA or A ratings. • High rated banks are characterised by high other operating income-to-average asset ratio (profitability), equity to customer-and-short-term funding ratio (capital strength) and equity-to-total asset ratio (capital strength); and low net loans-to-total assets ratios (liquidity) and low net loans-to-customer and short-term funding ratio (liquidity). • Banks with high loan loss reserves-to-gross loans ratios (poor asset quality) tend to obtain poor bank ratings.

		1993-2007. **Method**: Feature selection, cumulative probability distribution approach, rough set theory.	• Diversification of bank operations is an important factor for receiving a high bank rating.
Laere et al. (2012)	To examine whether the differences in ratings between Moody's and S&P are to the result of (1) the use of different standards, (2) systematic differences in ratings procedures and/or (3) random variations in judgement. This paper also investigated whether RAs have employed different rating models after the criticism of their activity during the global financial crises.	**Dependent variable**: S&P's (AAA to D) and Moody's (Aaa to C) long-term bank rating (bank ability to satisfy financial obligations as they come due) coded as 17 ordinal values (assigned 1 to AAA/Aaa and 17 to CCC+/Caa1 and below). **Independent variables**: Ratio of common equity to total assets as a proxy for capital adequacy, the ratio of loan loss provisions to loans as a proxy for asset quality, the ratio of cost to income ratio as a proxy for management quality, return on equity as a proxy for earning performance, the ratio of loans to deposits and the ratio of liquid assets to total assets as proxies for liquidity, ln assets as proxy for bank size, the ratio of non-interest expense to net income as a proxy for revenue diversification, ln [(ROA+EA)/ σ (ROA)] as a proxy for bank risk where ROA is the rate of return on assets, EA is the ratio of equity to total assets and σ (ROA) is an estimate of standard deviation of the ROA, SR as a proxy for country risk, the 3-month treasury rate as a proxy for business cycle and loan growth variable.	• SR is the most important determinant of bank ratings for both RAs. Thus, banks located in countries with high SRs have a better chance of obtaining a better rating. • The empirical results revealed that bank size, profitability, liquidity and asset quality contribute positively to bank rating. In addition, banks with lower default risk have a higher probability of acquiring a better bank rating. • The results also indicate that in response to the latest financial crises, Moody's and S&P have two different bank creditworthiness standards for a particular rating grade. However, both RAs employed similar standards of bank creditworthiness for the various rating classes prior to the global financial crisis. In general, S&P has implemented stricter bank rating standards than Moody's. • Both RAs use less prudence to assign ratings to large, profitable banks and/or banks with more loans in their portfolios.

		Sample: This paper used two samples: (1) 288 commercial banks from 40 countries that received a rating from both Moody's and S&P for the period from 2000 to 2011 for split-rating examination; (2) 505 and 552 commercial banks from 40 countries that received a rating from Moody's or S&P, respectively, for the period from 2000 to 2011 **Methodology**: heteroscedastic ordered probit model.	
Öğüt et al. (2012)	To predict Moody's BFSRs using the most important publicly available financial and operational variables and to examine whether or not the financial strength ratings developed by the prediction models in this study were consistent with those issued by RAs.	**Dependent variable:** Moody's BFSR coded on six rating categories: E = 1, E+ = 2, D- = 3, D = 4, D+ = 5 and C = 6. **Independent variables:** Ratio of total equity to total assets, total loans to total assets, nonperforming loans to total loans, non-current assets to total assets, liquid assets to total assets, liquid assets in foreign currency to total liabilities in foreign currency, net period income to total assets, net income to equity, interest revenues to interest expenses, total deposits to total assets, net interest revenues (loss) to number of branches, net interest revenue (loss) to total assets, net interest revenue (loss) to number of employees, total loans to total deposits, net interest revenue to total revenue from operations, non-interest revenue to total assets, assets to total assets	• Ordered logistic regression achieved the highest accuracy rate when using factor scores as input variables compared to other classifiers. Accuracy rates were highest for multiple discriminant analysis and support vector machine when financial and operational variables were used as input variables. • The prediction accuracy rate of classifiers using financial and operational variables as input variables was higher than using factor scores. • The empirical results revealed that banks with high loan portfolio (loan to asset ratio and loan to deposit ratio), profitability (return on equity), efficiency ratios (the ratio of net interest revenues [loss] to number of branches, the ratio of net interest revenue [loss] to total assets and

		of the sector, loans to total loans of the sector, deposits to total deposits of the sector, number of branches to total branches of the sector, number of employees to total number of employees of the sector, personal deposits to total deposits, foreign branches to total branches, specialised loans to total loans and assets in foreign currency to liabilities in foreign currency. **Sample:** 17 Turkish banks for the period from 2003 to 2009. **Methodology**: Multiple discriminant analyses, ordered logistic regression, support vector machine and artificial neural network.	the ratio of net interest revenue (loss) to number of employees) tend to obtain high ratings. • A piece of information derived from this study is that RAs assign low ratings to banks that invest more of their funds (especially deposits) in government debt securities rather than selling loans. This is mainly because investment in government debt securities results in low profitability and high market risk (mainly the interest rate risk).

Author	Objectives	Methods	Main Results
Hammer et al. (2012)	To construct a reverse-engineering Fitch bank rating model to evaluate the creditworthiness of banks.	**Dependent variable:** Fitch's FBRs coded on nine rating categories. **Independent variables:** *14 financial variables*: loans, other earning assets, total earning assets, non-earning assets, total assets, net interest revenue, customer and short-term funding, overheads, equity, net income, operating income, total liabilities and equity, profit before tax and other operating income. *9 financial ratios*: ratio of equity to total assets as proxy for asset quality; return on average assets, return on average equity, net interest margin, the ratio of interest revenue to average assets, operating income to average assets as proxies for profit efficiency; the ratio of non-interest expenses to average assets and cost-to-income ratio as proxies for cost efficiency; the ratio of net loans to total assets as a proxy for liquidity. S&P's country risk rating as a proxy for country risk. **Sample**: 800 banks rated by Fitch and operating in 70 countries as of December 2001. **Methodology**: Multiple linear regression, ordered logistic regression, support vector machine and logical analysis of data.	• This study reveals that logical analysis of data and ordered logistic regression are better than multiple linear regression and support vector machine in providing the most accurate results for a reverse-engineered Fitch bank rating system. • Comparison of the logical analysis of data and ordered logistic regression ratings with the Fitch ratings revealed that the classification accuracy associated with logistic analysis of data outperforms that of ordered logistic regression. • A piece of information derived from this study is that the logical analysis of data approach is suitable for reverse-engineering bank ratings as it is a objective, transparent and generalisable approach. These features can help bank mangers to construct internal rating systems that act in accordance with the IRB requirements and are consistent with Basel II requirements.

Author	Objectives	Methods	Main Results
Shen et al. (2012)	To investigate why banks with similar financial ratios located in different countries receive different credit ratings by proposing an information asymmetry hypothesis.	**Dependent variable:** S&P's long-term credit rating. **Independent variables:** Average ratio of net income to total assets as proxy for profitability; average ratio of liquid assets to deposits and short-term funding as proxy for liquidity; capital adequacy ratio as proxy for capital; the average cost-to-income ratio as a proxy for efficiency; average ratio of loan loss provisions to net interest revenues as a proxy for quality; natural logarithm of total assets as proxy for bank size; S&P's sovereign credit rating as proxy for country-specific effect; information disclosure quality as a proxy for asymmetric information and law and order tradition of a country, the quality of bureaucracy of a country and a country's corruption level as proxies for the institutional environment quality of a country. **Sample:** Rated banks in 86 countries from various regions during the period from 2002 to 2008. **Methodology**: Ordered probit model.	• RAs assign greater weight to banks' financial ratios in high-income and industialised countries because of low information asymmetry, better institutional environment quality and high quality financial statements. On the contrary, the weight of banks' financial ratios is minimal in middle-income countries because of a lack of transparency, high information asymmetry and low quality financial statements. • Improvements in banks' credit ratings are associated with countries having low information asymmetry. • The empirical results revealed that well-capitalised, highly liquid and profitable banks tend to obtain high ratings. Banks also tend to receive high ratings when the cost-to-income ratio (efficiency) and the ratio of loan loss provision to net interest revenues (quality) reach minimal levels. • The results showed that large banks located in countries with high sovereign credit ratings tend to receive high bank credit ratings.

Appendix B: Descriptive Statistics for Dependent and Explanatory Variables for Low- and Near-Low FSRs

Asset Quality Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
FSR	10.621	0.091	11.000	11.000	1.554	2.416	1.063	-1.248	6.000	6.000	12.000
LLPNIR	0.267	0.037	0.132	0.000	0.623	0.388	121.131	9.457	9.123	-0.438	8.685
LLRIL	0.904	0.025	0.850	0.891	0.388	0.151	5.810	1.786	2.899	0.095	2.994
ILGL	0.140	0.009	0.096	0.065	0.147	0.022	9.446	2.625	1.041	0.006	1.046
NCONIBLLP	0.184	0.049	0.054	0.000	0.683	0.467	70.663	7.712	7.907	-0.514	7.393
ILE	0.601	0.059	0.318	#N/A	0.920	0.847	17.927	3.830	6.967	0.028	6.995
UILE	0.295	0.050	0.101	#N/A	0.655	0.429	44.764	5.840	6.328	0.000	6.328

Credit Risk Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
COAGL	0.007	0.001	0.003	0.000	0.020	0.000	40.845	5.116	0.235	-0.044	0.191
LLPTL	0.015	0.001	0.008	0.000	0.023	0.001	8.871	2.711	0.164	-0.017	0.147
LLPE	0.071	0.008	0.027	0.000	0.139	0.019	15.557	3.508	1.292	-0.238	1.055
LLRGL	0.111	0.005	0.083	#N/A	0.088	0.008	2.219	1.519	0.462	0.013	0.475
LLRE	0.494	0.037	0.276	#N/A	0.634	0.402	5.932	1.949	5.030	-1.698	3.333

Control Variables	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
T	4.769	0.148	5.000	5.000	2.523	6.365	-1.144	0.121	8.000	1.000	9.000
SR	10.776	0.238	11.000	11.000	4.045	16.361	-1.226	-0.051	9.000	3.000	12.000
Size	1.417	0.038	1.000	1.000	0.640	0.410	0.432	1.268	2.000	1.000	3.000
Country	5.545	0.174	6.000	1.000	2.967	8.802	-1.174	-0.279	9.000	1.000	10.000

Capital Adequacy Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
TR	0.160	0.003	0.153	0.160	0.051	0.003	3.907	1.350	0.399	0.003	0.402
TCR	0.100	0.003	0.101	0.108	0.053	0.003	4.127	1.515	0.408	0.007	0.415
CS	0.109	0.004	0.113	0.109	0.069	0.005	5.644	-0.278	0.681	-0.383	0.298
ENL	0.238	0.005	0.227	0.279	0.079	0.006	4.633	1.415	0.667	0.011	0.678
EL	0.144	0.005	0.127	0.087	0.093	0.009	2.967	0.947	0.820	-0.239	0.582
EDSTF	0.155	0.006	0.135	0.166	0.105	0.011	4.583	0.681	1.045	-0.384	0.661
CFTA	0.114	0.006	0.110	0.110	0.072	0.005	8.424	-1.095	0.648	-0.314	0.334
CFNL	0.249	0.006	0.232	0.359	0.078	0.006	2.052	1.106	0.541	0.035	0.576
CFDSTF	0.144	0.008	0.128	#N/A	0.103	0.011	5.659	-0.139	0.900	-0.384	0.516
CFL	0.136	0.007	0.123	0.124	0.091	0.008	3.257	0.472	0.741	-0.239	0.502
SDCF	0.059	0.008	0.000	0.000	0.091	0.008	1.960	1.614	0.373	0.000	0.373
EM	10.572	0.355	8.738	#N/A	6.044	36.535	1.351	1.082	40.480	-7.117	33.363

Liquidity Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
IBR	1.683	0.104	1.188	#N/A	1.650	2.721	7.121	2.475	9.631	0.024	9.655
LR	0.547	0.007	0.551	0.642	0.116	0.013	-0.140	-0.190	0.615	0.201	0.816
NLDSTF	0.692	0.010	0.688	0.677	0.171	0.029	0.258	0.351	0.975	0.241	1.215
NLTDB	0.650	0.009	0.654	0.645	0.147	0.022	-0.094	-0.087	0.757	0.227	0.984
LADSTF	0.331	0.009	0.308	#N/A	0.157	0.025	-0.412	0.494	0.721	0.050	0.771
LATDB	0.313	0.010	0.288	0.178	0.156	0.024	-0.187	0.635	0.728	0.044	0.771

Profitability Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
NIM	0.030	0.001	0.030	0.037	0.009	0.000	8.781	1.550	0.079	0.010	0.089
NIRAA	0.029	0.001	0.028	0.031	0.012	0.000	-0.406	0.081	0.060	-0.001	0.059
OOIAA	0.016	0.001	0.013	0.015	0.014	0.000	25.762	4.315	0.125	-0.008	0.117
NIEAA	0.025	0.001	0.022	0.016	0.013	0.000	14.360	2.743	0.118	0.006	0.124
PTOIAA	0.017	0.001	0.014	0.025	0.017	0.000	12.822	1.754	0.191	-0.060	0.132
NOITAA	-0.003	0.000	-0.002	0.000	0.005	0.000	10.024	1.314	0.045	-0.018	0.028
ROAA	0.018	0.001	0.016	0.000	0.016	0.000	11.029	1.186	0.192	-0.061	0.132
ROAE	0.154	0.009	0.143	0.000	0.148	0.022	39.553	4.356	2.099	-0.536	1.563
DPO	0.452	0.048	0.434	0.000	0.645	0.416	61.933	-4.144	10.385	-6.000	4.385
INODAE	0.075	0.006	0.070	0.044	0.083	0.007	16.480	-1.579	0.875	-0.536	0.339
NOINI	0.080	0.045	0.000	0.000	0.598	0.357	21.445	3.886	5.646	-1.574	4.072
CIR	0.465	0.016	0.434	#N/A	0.280	0.078	134.987	9.769	4.296	0.098	4.393
REP	0.026	0.001	0.024	0.031	0.016	0.000	8.281	1.900	0.144	-0.010	0.134
NPM	0.241	0.012	0.210	#N/A	0.192	0.037	5.782	-0.817	1.716	-0.840	0.877
AU	0.062	0.001	0.061	#N/A	0.017	0.000	12.503	2.225	0.153	0.030	0.184
TME	0.805	0.042	0.881	1.000	0.705	0.497	124.084	-10.476	10.083	-8.500	1.583
ECE	0.270	0.012	0.263	0.333	0.193	0.037	7.086	-1.119	1.842	-0.961	0.881
OER	0.767	0.012	0.793	#N/A	0.190	0.036	4.172	0.852	1.483	0.228	1.711

Appendix C: Descriptive Statistics for Dependent and Explanatory Variables for High- and Near-High FSRs

Asset Quality Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
FSR	14.824	0.067	15.000	15.000	1.118	1.250	-0.485	0.212	4.000	13.000	17.000
LLPNIR	0.174	0.016	0.102	0.000	0.269	0.072	38.415	5.078	3.008	-0.232	2.776
LLRIL	1.392	0.042	1.238	2.000	0.687	0.472	9.277	2.428	5.482	0.341	5.823
ILGL	0.040	0.003	0.025	0.012	0.043	0.002	9.663	2.744	0.303	0.000	0.303
NCONIBLLP	0.114	0.029	0.026	0.000	0.447	0.200	108.270	9.315	6.693	-1.000	5.693
ILE	0.191	0.016	0.114	0.075	0.259	0.067	41.176	5.116	2.813	0.003	2.817
UILE	0.134	0.050	0.026	#N/A	0.426	0.181	43.503	6.289	3.266	0.000	3.266

Credit Risk Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
NCOAGL	0.005	0.001	0.001	0.000	0.015	0.000	56.068	6.823	0.161	-0.011	0.151
LLPTL	0.007	0.001	0.005	0.000	0.009	0.000	24.199	3.589	0.093	-0.005	0.088
LLPE	0.067	0.032	0.022	0.000	0.526	0.277	273.868	16.490	8.814	-0.032	8.782
LLRGL	0.044	0.002	0.035	#N/A	0.038	0.001	10.844	2.825	0.284	0.004	0.288
LLRE	0.240	0.035	0.150	#N/A	0.587	0.344	219.255	14.069	9.417	0.015	9.432

Control Variables	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
T	5.266	0.157	5.000	9.000	2.615	6.839	-1.249	-0.147	8.000	1.000	9.000
SR	14.932	0.129	15.000	17.000	2.146	4.605	1.378	-1.359	9.000	8.000	17.000
Size	2.381	0.041	2.000	3.000	0.679	0.461	-0.681	-0.644	2.000	1.000	3.000
Country	3.140	0.134	2.000	2.000	2.230	4.973	-0.043	1.034	8.000	1.000	9.000

Capital Adequacy Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
TR	0.176	0.006	0.159	0.117	0.079	0.006	8.471	2.220	0.559	0.061	0.620
TCR	0.208	0.006	0.187	0.129	0.091	0.008	4.192	1.743	0.590	0.080	0.670
CS	0.125	0.002	0.120	0.124	0.036	0.001	3.452	1.207	0.360	0.008	0.368
ENL	0.351	0.017	0.281	#N/A	0.292	0.085	8.828	2.575	2.409	-0.533	1.877
EL	0.146	0.003	0.137	0.122	0.050	0.002	5.850	1.742	0.417	0.008	0.425
EDSTF	0.160	0.003	0.148	#N/A	0.055	0.003	4.976	1.698	0.440	0.008	0.448
CFTA	0.130	0.003	0.127	0.109	0.035	0.001	4.555	1.314	0.274	0.024	0.298
CFNL	0.351	0.027	0.275	#N/A	0.327	0.107	8.466	2.519	2.409	-0.533	1.877
CFDSTF	0.168	0.004	0.157	0.144	0.058	0.003	5.933	1.855	0.422	0.026	0.448
CFL	0.151	0.004	0.145	0.122	0.049	0.002	7.469	1.942	0.400	0.025	0.425
SDCF	0.095	0.010	0.104	0.000	0.107	0.011	6.010	1.613	0.685	0.000	0.685
EM	8.947	0.456	8.350	#N/A	7.609	57.893	234.876	14.712	126.842	3.353	130.195

Liquidity Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
IBR	3.468	0.165	2.711	#N/A	2.350	5.521	-0.146	0.844	9.874	0.032	9.907
LR	0.435	0.012	0.439	#N/A	0.210	0.044	-1.234	-0.035	0.779	0.041	0.820
NLDSTF	0.552	0.017	0.551	#N/A	0.292	0.085	-0.846	0.145	1.516	0.046	1.562
NLTDB	0.526	0.018	0.510	#N/A	0.268	0.072	-1.067	0.176	1.157	0.046	1.202
LADSTF	0.416	0.010	0.389	#N/A	0.170	0.029	0.121	0.607	0.935	0.009	0.943
LATDB	0.395	0.010	0.379	#N/A	0.158	0.025	0.487	0.678	0.888	0.056	0.943

Profitability Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
NIM	0.032	0.001	0.033	0.044	0.013	0.000	-0.280	-0.183	0.063	-0.001	0.062
NIRAA	0.028	0.000	0.027	0.024	0.008	0.000	9.488	1.625	0.071	0.010	0.081
OOIAA	0.016	0.001	0.014	0.016	0.011	0.000	56.272	5.829	0.149	-0.007	0.142
NIEAA	0.019	0.001	0.018	0.018	0.009	0.000	8.753	2.227	0.070	0.005	0.075
PTOIAA	0.024	0.001	0.023	0.035	0.015	0.000	20.846	1.506	0.197	-0.059	0.139
NOITAA	-0.002	0.000	-0.001	-0.001	0.005	0.000	19.727	-3.293	0.046	-0.035	0.011
ROAA	0.023	0.001	0.022	0.017	0.014	0.000	18.320	0.385	0.204	-0.072	0.132
ROAE	0.178	0.008	0.185	0.209	0.135	0.018	63.076	-5.918	1.906	-1.360	0.546
DPO	0.440	0.016	0.426	0.000	0.249	0.062	-0.640	0.132	1.137	0.000	1.137
INODAE	0.104	0.006	0.097	0.067	0.088	0.008	8.414	-0.750	0.864	-0.394	0.470
NOINI	-0.063	0.026	-0.008	0.000	0.355	0.126	12.380	-1.274	3.582	-2.052	1.530
CIR	0.346	0.006	0.342	0.291	0.097	0.009	0.378	0.478	0.532	0.164	0.696
REP	0.029	0.001	0.028	0.020	0.012	0.000	25.831	3.206	0.133	0.007	0.140
NPM	0.335	0.012	0.368	#N/A	0.187	0.035	21.388	-3.410	1.891	-1.208	0.683
AU	0.073	0.001	0.071	#N/A	0.019	0.000	9.685	1.609	0.175	0.022	0.197
TME	0.971	0.004	1.000	1.000	0.061	0.004	5.568	-2.415	0.362	0.713	1.075
ECE	0.345	0.012	0.374	#N/A	0.185	0.034	22.810	-3.587	1.890	-1.207	0.683
OER	0.651	0.011	0.619	#N/A	0.164	0.027	19.271	2.969	1.705	0.283	1.988

Appendix D: Descriptive Statistics for Dependent and Explanatory Variables for All FSRs

Asset Quality Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
FSR	12.678	0.105	12.000	12.000	2.503	6.265	-0.381	-0.352	11.000	6.000	17.000
LLPNIR	0.221	0.020	0.113	0.000	0.482	0.232	174.260	10.811	9.123	-0.438	8.685
LLRIL	1.162	0.027	1.023	2.000	0.616	0.379	10.675	2.476	5.728	0.095	5.823
ILGL	0.087	0.005	0.044	0.012	0.117	0.014	16.982	3.455	1.046	0.000	1.046
NCONIBLLP	0.146	0.027	0.033	0.000	0.568	0.322	90.338	8.625	8.393	-1.000	7.393
ILE	0.384	0.031	0.180	0.075	0.689	0.475	34.112	5.139	6.991	0.003	6.995
UILE	0.248	0.038	0.076	#N/A	0.601	0.361	48.693	6.078	6.328	0.000	6.328

Capital Adequacy Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
TR	0.167	0.003	0.154	0.160	0.065	0.004	9.930	2.216	0.617	0.003	0.620
TCR	0.193	0.003	0.176	0.178	0.074	0.006	6.611	2.047	0.663	0.007	0.670
CS	0.123	0.002	0.119	0.109	0.055	0.003	8.295	-0.198	0.751	-0.383	0.368
ENL	0.296	0.009	0.248	0.279	0.223	0.050	17.942	3.578	2.409	-0.533	1.877
EL	0.145	0.003	0.135	0.122	0.075	0.006	4.981	1.147	0.820	-0.239	0.582
EDSTF	0.157	0.004	0.145	0.167	0.084	0.007	6.859	0.854	1.045	-0.384	0.661
CFTA	0.123	0.003	0.122	0.109	0.056	0.003	13.082	-1.192	0.648	-0.314	0.334

Capital Adequacy Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
CFNL	0.296	0.013	0.242	0.359	0.234	0.055	19.960	3.742	2.409	-0.533	1.877
CFDSTF	0.157	0.005	0.151	0.144	0.082	0.007	8.018	-0.014	0.900	-0.384	0.516
CFL	0.144	0.004	0.139	0.122	0.072	0.005	5.536	0.590	0.741	-0.239	0.502
SDCF	0.077	0.006	0.000	0.000	0.101	0.010	4.620	1.623	0.685	0.000	0.685
EM	9.777	0.289	8.426	#N/A	6.897	47.566	164.159	9.905	137.312	-7.117	130.195

Credit Risk Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
NCOAGL	0.006	0.001	0.002	0.000	0.017	0.000	47.866	5.845	0.235	-0.044	0.191
LLPTL	0.011	0.001	0.006	0.000	0.018	0.000	16.490	3.550	0.164	-0.017	0.147
LLPE	0.069	0.016	0.024	0.000	0.384	0.147	477.785	21.119	9.019	-0.238	8.782
LLRGL	0.078	0.003	0.050	#N/A	0.076	0.006	4.915	2.092	0.471	0.004	0.475
LLRE	0.369	0.026	0.204	#N/A	0.624	0.389	82.595	6.808	11.129	-1.698	9.432

Liquidity Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
IBR	2.481	0.102	1.700	#N/A	2.180	4.753	1.431	1.430	9.883	0.024	9.907
LR	0.490	0.008	0.517	0.642	0.180	0.032	-0.536	-0.499	0.779	0.041	0.820
NLDSTF	0.620	0.011	0.647	0.937	0.250	0.063	-0.261	-0.202	1.516	0.046	1.562
NLTDB	0.592	0.010	0.609	0.645	0.222	0.049	-0.473	-0.301	1.157	0.046	1.202
LADSTF	0.375	0.007	0.347	0.458	0.169	0.029	0.032	0.565	0.935	0.009	0.943
LATDB	0.352	0.007	0.332	0.178	0.162	0.026	0.142	0.606	0.900	0.044	0.943

Control Variables	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
T	5.012	0.108	5.000	7.000	2.578	6.647	-1.226	-0.007	8.000	1.000	9.000
SR	12.810	0.162	14.000	16.000	3.862	14.913	-0.602	-0.774	14.000	3.000	17.000
Size	1.889	0.034	2.000	1.000	0.817	0.667	-1.471	0.207	2.000	1.000	3.000
Country	4.368	0.121	4.000	1.000	2.892	8.363	-1.226	0.361	9.000	1.000	10.000

Profitability Category	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum
NIM	0.031	0.000	0.031	0.026	0.011	0.000	1.751	0.357	0.090	-0.001	0.089
NIRAA	0.028	0.000	0.028	0.028	0.010	0.000	1.728	0.500	0.082	-0.001	0.081
OOIAA	0.016	0.001	0.014	0.010	0.013	0.000	36.036	4.903	0.150	-0.008	0.142
NIEAA	0.022	0.000	0.019	0.016	0.012	0.000	15.448	2.791	0.119	0.005	0.124
PTOIAA	0.021	0.001	0.020	0.025	0.017	0.000	14.331	1.480	0.198	-0.060	0.139
NOITAA	-0.003	0.000	-0.002	-0.001	0.005	0.000	13.373	-0.747	0.063	-0.035	0.028
ROAA	0.020	0.001	0.020	0.000	0.015	0.000	12.897	0.779	0.204	-0.072	0.132
ROAE	0.166	0.006	0.165	0.000	0.142	0.020	46.531	0.041	2.923	-1.360	1.563
DPO	0.445	0.022	0.429	0.000	0.463	0.214	100.412	-4.754	10.385	-6.000	4.385
INODAE	0.091	0.004	0.085	0.067	0.087	0.008	10.877	-0.995	1.006	-0.536	0.470
NOINI	0.008	0.026	-0.004	0.000	0.494	0.244	26.552	3.320	6.124	-2.052	4.072
CIR	0.407	0.009	0.384	0.291	0.219	0.048	193.135	10.917	4.296	0.098	4.393
REP	0.027	0.001	0.027	0.020	0.015	0.000	12.844	2.202	0.149	-0.010	0.140
NPM	0.287	0.009	0.316	#N/A	0.195	0.038	10.369	-1.879	2.085	-1.208	0.877
AU	0.067	0.001	0.067	#N/A	0.019	0.000	9.132	1.733	0.175	0.022	0.197
TME	0.887	0.021	0.988	1.000	0.510	0.260	238.272	-14.407	10.083	-8.500	1.583
ECE	0.307	0.009	0.335	0.333	0.192	0.037	12.249	-2.153	2.088	-1.207	0.881
OER	0.710	0.008	0.683	#N/A	0.187	0.035	7.126	1.559	1.759	0.228	1.988

Appendix E: Analysis of Model-Fitting Criteria and Likelihood Ratio Tests for Logistic Regression Model

Model	Model-Fitting Criteria	Likelihood Ratio Tests		
	2 Log Likelihood	Chi-Square	Df	Sig.
Intercept only	335.741			
Final	10.806	324.936	18	.000